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Structural dynamics of keyword networks: Liquid crystal display and plasma display panel cases

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ABSTRACT

This study focuses on understanding scientific evolution by using keyword co-occurrence networks, where keywords appearing in a scientific article are linked with a weight equal to the number of co-occurrences. To characterize structural changes of the network, we examine distributions of sums of weights by node over time. In particular, a change of power-law behavior is utilized to explore scientific evolution, such as emerging scientific paradigms and advancing normal science. As an illustration of the method used, the development of Liquid Crystal Displays (LCDs) and Plasma Display Panels (PDPs) is tracked. We detect two-tiered power-law distributions in the initial stage of scientific growth in both technologies due to differences in research intensity between two groups. The groups of keywords more likely to attract researchers' interest than others are incrementally developed until the mid-2000s to overtake those prior. Finally, we can capture a merging point of the dichotomous structure of PDPs but LCDs maintain the structural separation throughout the adjustment area. We expect that this structural investigation of keyword co-occurrence networks provides an indicator to diagnose the research evolution in that field.

1. Introduction

Thomas Kuhn, a famous science philosopher, described scientific revolution as a paradigm shift (Kuhn, 1996). After the emergence of the paradigm shift, a puzzle-solving process follows to enrich the discipline through incremental development. The concept of Kuhn's notion of paradigms and the process of technological diffusion (Abernathy and Utterback, 1978) are two of a kind. Noting the similarity between scientific and technological principles, the scholarly community saw them as having a stable "knowledge base" (Anderson and Tushman, 1990; Murmann and Frenken, 2006; Clark, 1987). Stable components that are widely adopted in an industry are called "dominant designs" (Abernathy and Utterback, 1978) or a body of technology by Arthur (2009).

The emergence of dominant design is accepted as a critical juncture in the evolution of an industry because it changes the nature of competition within the corresponding industry. As a successful variation, a dominant design leads technical progress from variational to incremental improvements. Similar to scientific paradigms, dominant designs need to be

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elaborated by incremental evolution. In the technology-cycle concept, the dominant design-induced competitive environment changes are recurrent patterns; variations (technological discontinuity), the selection of a dominant design, and incremental innovations (Anderson and Tushman, 1990).

Recently, structural changes in science and technology over time have intrigued scholars (Viana et al., 2013; Kim et al., 2012; Shibata et al., 2007; Chen 2004; Hwang 2008; Morris et al., 2003). Takeda and Kajikawa (2010) revealed that components of related nodes in citation networks also follow similar trajectories to those of scientific evolution. The authors have explained the development of science and technology through core/periphery structures that signify a small number of core nodes are well connected to each other with a large number of links compared to peripheral nodes (Zhou and Mondragon, 2004; Serrano, 2008). While Clymer and Asaba, (2008) used their own taxonomy to identify dominant designs of a technology, Murmann and Frenken (2006) proposed a model that distinguishes the stable knowledge base as core components in complex systems. Most of these studies argued that after constructing a core component, peripheral components are developed. However, in contrast to the well formulated theories of scientific evolution, Fleming and Sorenson (2001) pointed out a lack of systematic and empirical validations.

This paper aims to ascertain the change in the structure of scientific knowledge through a keyword co-occurrence network. As one of the various relational bibliometric indicators, keyword co-occurrences deal with scientific knowledge itself (Zhang et al., 2012; Shibata et al., 2007). Although the keywords can be extracted from the title, abstract, or text (Assefa and Rorissa, 2013), we investigate the knowledge structure via author keywords. The keywords specified by authors, which particularly express researchers' interests and intentions, help us to grasp the key concept and the novelty of the research. Using the keyword co-occurrences; we generate a network where keywords found in a same document are connected to each other. We assign link weight based on the frequencies of keyword co-occurrences to identify the significance of relations between research issues. The concept of core/periphery is employed to explore the structural evolution of the keyword co-occurrence network.

In order to detect core groups, a specific method is also required because of ambiguous distinctions between the regimes in empirical data. We reveal the core/periphery structure based on the two-tiered power-law distribution functions among the various methods (Borgatti and Everett, 2000; Shanahan and Wildie, 2012; Colizza et al., 2006). We also try to explain robust evolution in science under the segregated system borrowing theory from other disciplines, such as complex systems, network sciences, and evolutionary biology. The change of this core/periphery structure helps us to observe empirical evidence for the evolution of knowledge structure as is.

As an illustration, we compare the technical progress between two representative technologies in Flat Panel Displays (FPDs) – Liquid Crystal Displays (LCDs) and Plasma Display Panels (PDPs) – because both technologies are stabilized along the technological trajectories in competition. Our results demonstrate that once a core is formed in the distribution of nodal sum of all co-occurrences, technologies take steps toward incremental expansion of the core. In the scientific progress, the research intensity differentiates the core. The separated structures inherent in the technologies reach different consequences over time. Each dichotomy between core and periphery turns into a single structure or maintain the structural separation throughout the area adjustment. Hence, the well-known theories on scientific evolution are materialized by this longitudinal study. The method used in this paper provides a groundwork for an empirical basis for scientific progress.

This paper opens by backgrounds and the purpose. The remainder of this paper is structured as follows. Section 2 delineates methods for construction of keyword co-occurrence networks and evolution of the core/periphery structure. Section 3 explains the data collection and network construction processes. Section 4 discusses the results obtained. Finally, Section 5 summarizes and concludes this paper.

2. Methods

This section explains the methods to generate a keyword co-occurrence network and the two-tiered power-law density functions that this paper employs to reveal the core/periphery structure. We introduce indicators to measure the evolution of a keyword co-occurrence network. To investigate the change in the knowledge structure through the keyword co-occurrence networks, we used the *R ver. 3.1.3* environment (R Core Team, 2015) and utilized add-on packages for convenience: *ggplot2* (Wickham 2009) and *igraph* (Csardi and Nepusz, 2006).

2.1. Construction of keyword co-occurrence networks

We connect any pair of keywords that both occurred within the same document to each other as depicted in Fig. 1. In this study, the network is a weighted undirected graph where the nodes are keywords specified by authors, links between nodes indicate the co-occurrence of two keywords, and the weight of a link refers to the frequency of the co-occurrences. In recent years, studies on network structure of research development have been expanding the use of weighted networks (Fujita et al., 2014). To describe an outdated reference to the older structure (Podolny et al., 1996), we generate the keyword co-occurrence networks by appending network components – nodes, links and weights – to the existing network every year.

To characterize knowledge structures in scientific systems, we measure structural properties of the keyword co-occurrence networks, such as nodes, links, density, and node strength. The numbers of nodes and links show the size of network. Network connectivity is described by network density, defined as the total number of links divided by the total

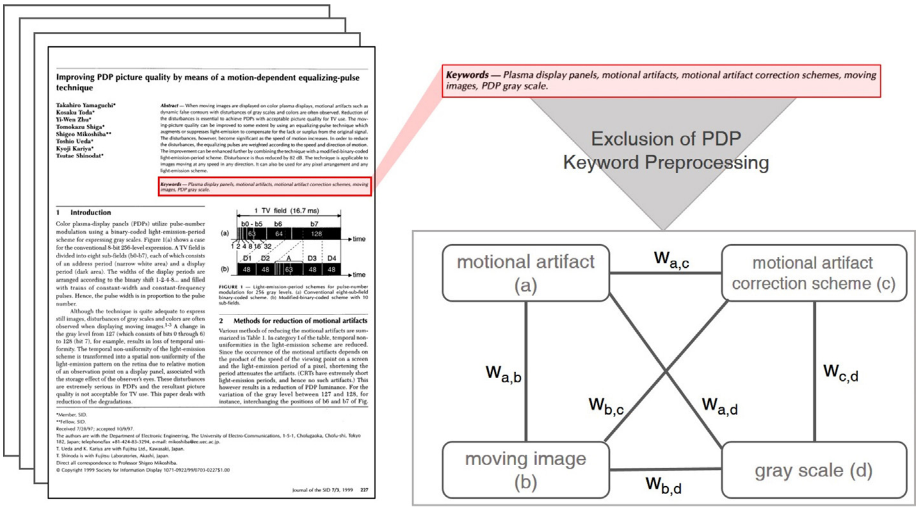


Fig. 1. Example of the construction of keyword co-occurrence network in PDP technology; $w_{i,j}$ represents the number of co-occurrences between keyword i and keyword j; Paper image is from Yamaguchi et al. (1999).

number of possible links. Furthermore, research intensity on a certain keyword can be characterized by node degree (same the number of links) or node strength, which implies the sum of weights connected to the node. The node degree is insufficient to capture the node importance in a weighted network, like the keyword co-occurrence network, because it just focuses on whether two keywords are connected or not. Opsahl et al. (2010) pointed out node degree in a non-weighted network, i.e. all link weights are equal to 1, is generally extended to node strength in a weighted network. Barrat et al. (2004) also emphasized node strength is a measure of the centrality of a node in a weighted network. We thus adopt node strength as a measure of node significance relative to other nodes.

2.2. Power-law distribution in keyword network

A quantity x follows a power-law if it satisfies the probability distribution $p(x) \propto x^{-\alpha}$, where α denotes a constant parameter of the distribution called an exponent or a scaling parameter. According to literature on complex systems, various natural phenomena and man-made systems, such as the populations of cities and the intensity of earthquakes (Clauset et al., 2009) exhibit power-law distributions. Relational bibliometric indicators such as keyword co-occurrences were fitted for the power-law distribution as well (Liu et al., 2012; Yi and Choi, 2012). There are many types of distributions to describe long-tail behaviors, such as Weibull distributions and log-normal distributions, but due to difficulties to differentiate between them, the investigations of long-tailed phenomena often address power-law distributions as its simplest form (Marković and Gros, 2014).

In the present study, we examine the long-tailed spread of node strengths in keyword co-occurrence networks. Previous studies argued that the distribution of node strength in most large networks has a long tail, highly skewed toward the right (Barrat et al., 2004) like the distribution of node degree (Newman 2003; Albert and Barabasi, 2002). The power-law distribution in this study implies that the network is composed of a small number of keywords with a large value of strength and a large number of nodes having a small node strength. The derived parameter α has a high possibility of being inaccurate in general power-law distribution owing to limited sample size. In order to handle the noise in the tail, the power-law distribution is thus usually represented as the cumulative distribution function (CDF) (Newman, 2003).

2.3. Identification of core-periphery structure

According to the notion of the core/periphery structure, a network can be divided into two realms: core and periphery. Nodes in the core group, which is also called the “rich-club,” have relatively a large number of links compared to the peripheral nodes. Links belonging to the core are each connected to other cores or peripheral nodes. In contrast to the core, peripheries are sparsely connected although the most part of a network comprises peripheral nodes. Chen and Guan (2016) found that such structural features were also contained in technological knowledge diffusion. When segmenting a weighted network into the core and periphery, node strength was utilized instead of node degree (Zlatic et al., 2009; Serrano, 2008). Previous studies noted that the core group retains a number of relations between peripheral nodes and performs an essential glue function in the network (Borgatti and Everett, 2000; da Silva et al., 2008; Holme 2005). There are different forms of core/periphery structures: specifically, nested networks (Saavedra et al., 2011), bow-tie structures in the directed network (Kitano, 2004), and onion network structures (Csermely et al., 2013).

In the present study, node strength is used to divide a network into core and periphery groups. We thus consider the core/periphery structure as being composed of two power-law distributions in accordance with a break point. Therefore, nodes in the core have a tendency to getting much higher values in node strength compared to the peripheral nodes. In other words, the dichotomized structures imply a possibility that each realm is affected by different mechanisms. Keywords within the core have more links or some links with a greater number of co-occurrences, or both, compared to nodes in the periphery. This structure is also called broken power-laws (Jóhannesson et al., 2006). Applying log-scaled piecewise linear regression, Zelnio (2012) estimated two-tiered distributions in international collaborations. The breakpoint signifies the position where the sum of squares is minimized for two log-scaled linear models (Toms and Lesperance, 2003).

An appropriate measure is also required to estimate suitability whether the distribution is fitted to the power-law distribution(s) or not. In principle, any goodness-of-fit measures can be used (Koen and Kondlo, 2009), but we employ the Kolmogorov–Smirnov (KS) test to determine the goodness-of-fit. The result of the KS test typically is more stable to the sample size than R^2 or other measures of goodness-of-fit when describing heavy-tailed data sets (Clauset et al., 2009; Marković and Gros, 2014). The *p*-value KS test determines statistical significance under the null hypothesis that two samples are drawn from the same distribution in contrast to R^2, which focuses on the error. If *p*-value is close to one, then the difference between the two samples can be influenced by statistical fluctuations alone; if it is small (close to zero), the estimated model is unsuitable for the data.

2.4. Evolution of core-periphery structure

We regard the core group in a distribution of node strengths to be a scientific paradigm. Previous studies argued that once the core components are formed, post development tends to focus on the peripheral components (Anderson and Tushman, 1990; Kuhn, 1996; Murmann and Frenken, 2006). Arthur (2009) also mentioned that technological progress provokes a change in the core, which results in an expansion of a core area. The growth of a core can be measured by the changes of indicators, such as an increase in core size and breakpoint. The core growing in the keyword network implies that researchers' attention to the marginal issues associated with the core is increasing.

In the literature on network sciences, these segregated structures are known to have robustness characteristics. According to Carlson and Doyle (2002), robustness signifies a system's capability to maintain the desired functions despite external and internal perturbations. An evolving system must be robust against unpredictable behaviors and environments. The stable process inherent in the core preserves the functions that other components co-select. Accordingly, the core/periphery structure is optimal to protect components and interactions from perturbations (Kitano, 2004). Therefore, on the basis of the robustness resident in the core/periphery structure, we can project the evolvability of the two technologies. The robustness mainly comes from the incremental growth of the core in science. In this regard, the succession rate of the core, the overlapping rate of keywords belonging to the previous core, can show the extent of accumulative growth of the core. In addition, transitions of density in the dichotomy provide information about how resistant each group is to failure of elements alongside the structural changes taking place in the keyword co-occurrence network.

We can also compare the power-law exponents between the core and the periphery. The differences of the exponents between the dichotomous structures indicate the inequality of research intensity. The different intensity between the two groups can be related to the origin of the core/periphery structures albeit its origin is still controversial (Kitano, 2004).

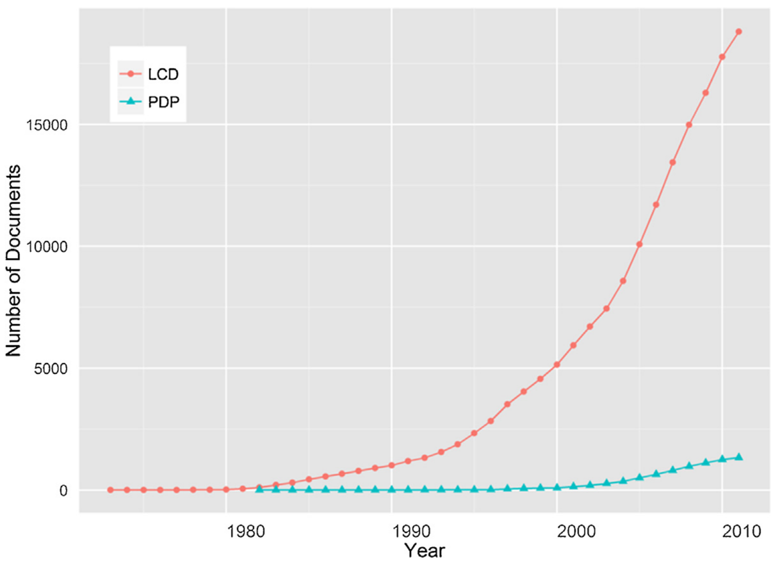


Fig. 2. Accumulated number of documents in LCD and PDP technologies from 1973 to 2011.

Dominant designs may emerge—the market power of a dominant producer, a powerful user, an industry committee, a firm alliance, or government regulation (Anderson and Tushman, 1990; Dosi, 1982). Stork (1991) pointed out that increasing centralization of interactions in a new research organization was associated with decreasing uncertainty experienced by scientists. Other scholars in complex network science contend that the dichotomy is caused by external "stress" (Estrada and Hatano, 2010), resource scarcity in the system (Carlson and Doyle, 2002), or "selective pressure" (Peixoto, 2012). An economic recession and competition between alternative technological orders could be regarded as examples of external stress and selective pressures, respectively. The poorer the system gets in resources, the smaller and tighter the cores that may evolve. As a result, a stable knowledge base develops through a combination of sociological, political, and organizational dynamics (Murmann and Frenken, 2006). Furthermore, the changes of power-law exponents from the segregated structures over time would help understand the intensity status of that scientific field.

3. Data collection and network generation

We acquired bibliographies from Elsevier's Scopus. Both full names and abbreviations were adopted as search terms, e.g. "liquid crystal display" and "LCD." To take into account academic mainstream and trends, document types were placed within articles and conference papers (Peters and van Raan, 1993). As regards LCD technologies, we observed that the first related document was published in 1973 (Scheffer, 1973), and the number of publications was 18,812, by 2011 as depicted in Fig. 2. Furthermore, the first article containing author keywords associated with LCD was published in 1975 (Volterra and

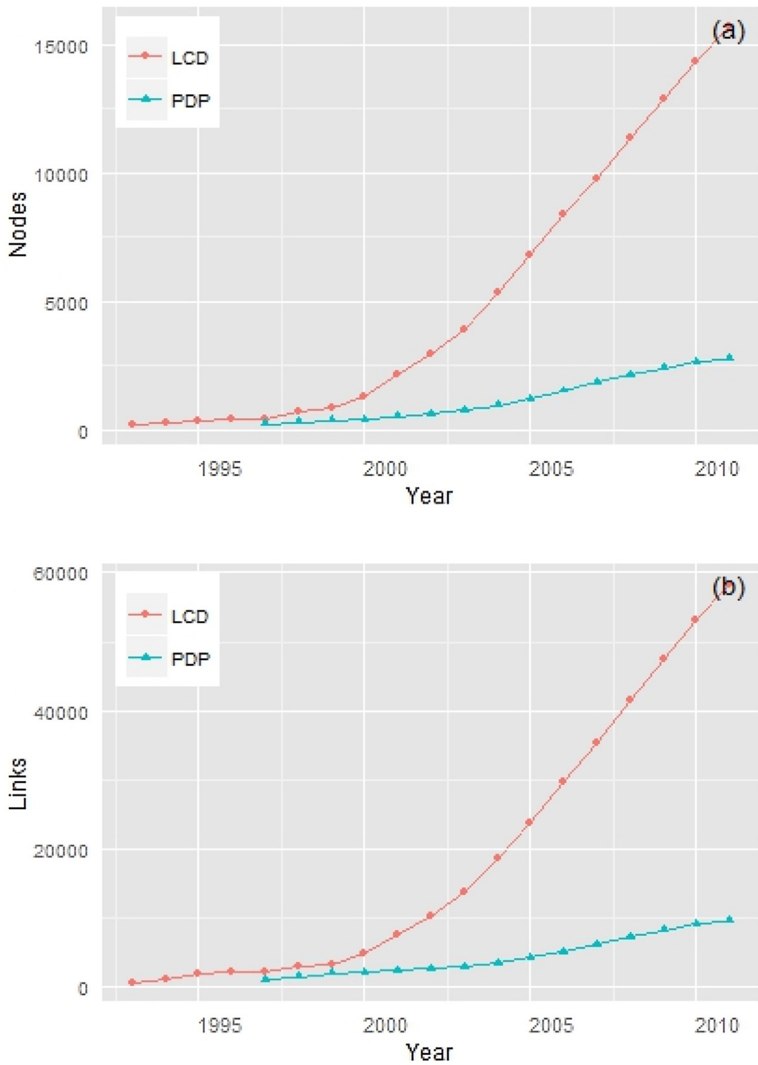


Fig. 3. Growth of keyword co-occurrence network over time: each network contains the accumulated (a) nodes (keywords) and (b) links (co-occurrences) from the first appearance of scientific documents in the corresponding year.

Wiener-Avnear, 1975), and the aggregate documents totaled 7255 in 2011. Publications associated with PDP initially appeared in 1982 (Boardman and Deschamps, 1982), and totaled 1334 documents by 2011, less than that of LCD.

For preprocessing, we manipulated keywords, such as lower-case, singular form, abbreviated form, contraction of multiple whitespaces, and removal of all punctuation (like hyphens and slashes). We used semicolons in the author keyword field to separate keywords, which represent nodes in the networks. The search terms, i.e., "LCD" and "PDP," were excluded from node construction.

4. Results and discussions

This section examines the structure of the keyword co-occurrence network and discusses the dynamics of the network structure with the progress and adoption of LCD and PDP. Although LCD and PDP are categorized as FPD, both technologies deliver light in different ways. More specifically, as a passive device, which does not produce any light for the display, LCDs implement fluorescent backlights. To produce images, LCDs manipulate the liquid crystal and align it in a certain pattern in response to an electric current. On the other hand, PDPs utilize pixels containing ionized gases, a form of matter called plasma. The current through the PDPs' screen produces ultraviolet light that reacts with the appropriate red, green, and blue phosphor in each pixel to emit visible light. Technological progress and adoption in an area can influence the development of other area in a way, and we compare the developmental dynamics via structural changes of keyword co-occurrence networks. Here, in order to assure statistical quality, the network analysis begins with an accumulation of keywords of over 100; the investigation of the LCD network starts in the period 1975–1992, while that of the PDP network is in the period 1982–1997.

In technological developments, superior performance is generally pursued in the early stages because innovation is crude and experimental. According to our results in Fig. 3, FPDs seems to be no exceptions because of the exponential growth in the number of nodes and links in each network. After the world's first pocket calculator using LCD was introduced in 1973, LCDs emerged as the clear leader owing to their lightweight and energy-efficient characteristics (Kawamoto, 2002). However, the slow response time resulting from the external light source used by LCDs is often unsuitable to refresh a video image. This fact, coupled with technological difficulties encountered in making LCDs larger than 32 inches, accelerated the introduction of PDPs into the market in the late 1990s (Uchikoga, 2006). PDPs attracted attention as a next-generation display technology suitable for the digital TV era. PDPs are used for outdoor billboards and wall-mountable TVs and are attributed with the superior image quality, quick response time, and feasibility of large-screen displays. However, their high prices and the large amounts of electricity they consume are a barrier to demand expansion. The shortcomings in one technology consequently spur the development of competing technologies.

Fig. 4(a) and (b) depict the change in LCD node strength distribution in complementary CDF (CCDF) form, and the transition depicted in Fig. 4 (c) and (d) is the case of PDP. The graphs depict the cumulative probability $p(x \geq x_i)$ of events

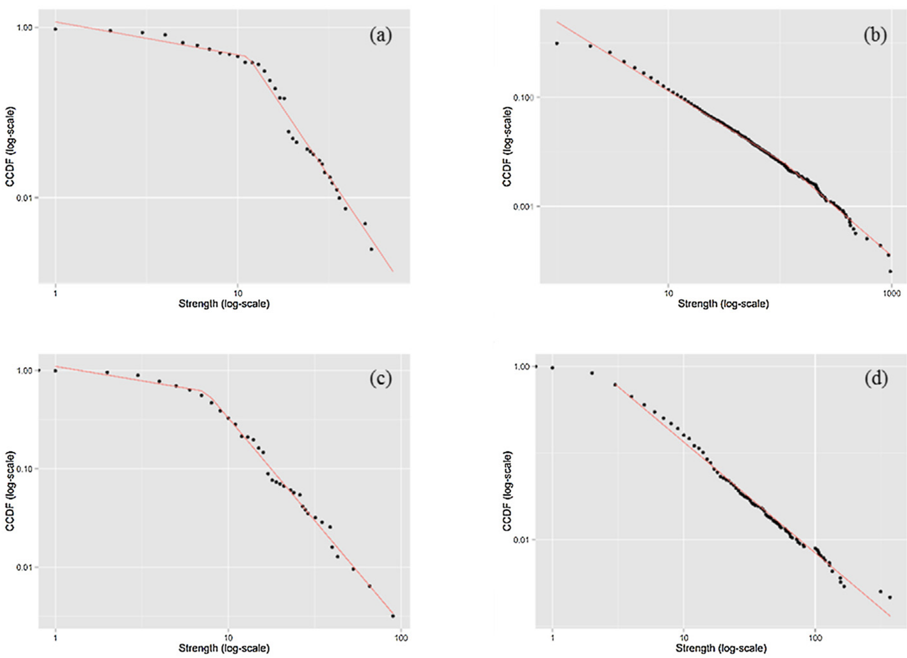


Fig. 4. Node strength complementary cumulative distribution function (CCDF): (a) LCD: 1975–1996, (b) LCD: 1975–2011, (c) PDP: 1982–1998, (d) PDP: 1982–2011.

Table 1
LCD core/periphery structure estimation.

Period	Break-point	Periphery				Core				Goodness-of-fit	
		Exponent[a]	Std error	*t*-stat	*p*-value[†]	Exponent[a]	Std error	*t*-stat	*p*-value[†]	KS test	*p*-value[‡]
1975–1992	22.08	3.05	0.46	−4.45	0.0043	−3.05	2.87	1.41	0.2077	0.47	0.98
1975–1993	14.24	1.75	0.07	−10.93	<0.0001	8.35	0.23	−32.19	<0.0001	0.32	0.9999
1975–1994	9.96	1.47	0.1	−4.67	0.0001	3.79	0.2	−14.28	<0.0001	0.42	0.9952
1975–1995	11.5	1.34	0.07	−5.09	<0.0001	3.91	0.12	−23.94	<0.0001	0.36	0.9995
1975–1996	11.41	1.39	0.08	−5.09	<0.0001	3.79	0.13	−20.72	<0.0001	0.36	0.9995
1975–1997	11.41	1.39	0.08	−5.09	<0.0001	3.79	0.13	−20.72	<0.0001	0.36	0.9995
1975–1998	11.5	1.59	0.1	−6.15	<0.0001	3.23	0.16	−13.95	<0.0001	0.34	0.9998
1975–1999	11.37	1.65	0.1	−6.76	<0.0001	3.04	0.16	−13.09	<0.0001	0.34	0.9998
1975–2000	10.71	1.74	0.07	−11.25	<0.0001	2.55	0.09	−16.35	<0.0001	0.31	1.0
1975–2001	8.41	1.74	0.05	−14.62	<0.0001	2.15	0.06	−18.37	<0.0001	0.27	1.0
1975–2002	6.21	1.64	0.07	−9.59	<0.0001	2.12	0.08	−14.58	<0.0001	0.26	1.0
1975–2003	6.12	1.65	0.08	−8.15	<0.0001	2.05	0.09	−11.75	<0.0001	0.4	0.9976
1975–2004	6.37	1.68	0.08	−8.4	<0.0001	1.96	0.09	−10.78	<0.0001	0.36	0.9994
1975–2005	7.07	1.77	0.08	−10.07	<0.0001	1.83	0.08	−9.78	<0.0001	0.41	0.9965
1975–2006	8.19	1.82	0.06	−12.78	<0.0001	1.75	0.07	−10.38	<0.0001	0.38	0.9985
1975–2007	9.64	1.86	0.05	−16.57	< .0001	1.69	0.06	−11.65	<0.0001	0.37	0.9993
1975–2008	129.48	2.32	0.01	−109.18	<0.0001	1.56	0.04	−15.65	<0.0001	0.23	1.0
1975–2009	146.35	2.32	0.01	−119.37	<0.0001	1.59	0.03	−16.87	<0.0001	0.28	1.0
1975–2010	145.95	2.31	0.01	−120.09	<0.0001	1.57	0.03	−17.65	<0.0001	0.38	0.9986
1975–2011	111.66	2.27	0.01	−107.01	<0.0001	1.51	0.03	−18.19	<0.0001	0.37	0.999

[a] Values are estimated exponent + 1 to compensate for decrease in linear regression on complementary cumulative distribution functions (CCDFs).
[†] *p*-values are produced by Student's *t*-test for a log-linear regression.
[‡] *p*-values are produced by Kolmogorov–Smirnov (KS) test.

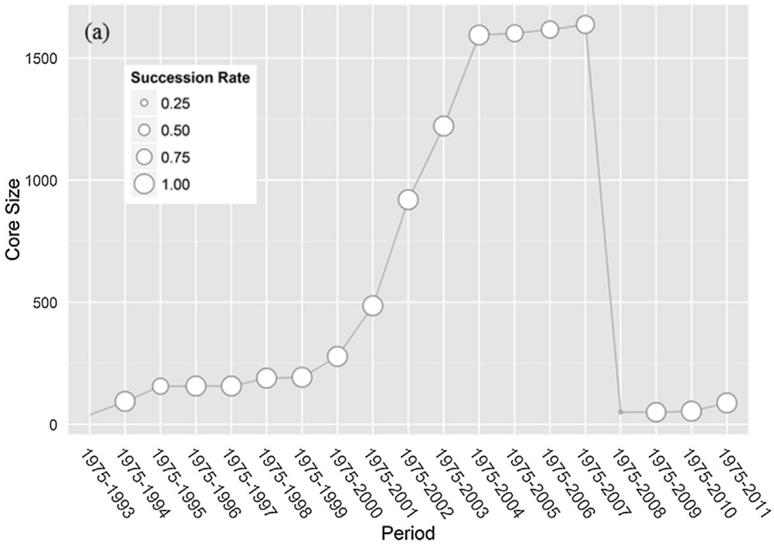
greater than or equal to a given node strength x_i. The power-law in CCDF also follows power-laws, but with exponent $\alpha - 1$ rather than α. Both axes in the distribution functions represent logarithmic scales. We considered over four node strengths to estimate the exponent since a paper embodies 3.74 keywords on average. The reason why we set a threshold of the distribution area is that the number of keywords included in a document varies. In order to except from the analysis, we established an interval difficult to accurately fit because of noise in the data. In other words, if the fitting model is statistically significant and the breakpoint of the core/periphery structure is set to under four node strengths, we can see the node strength distribution as a single power-law. In the early days, both distributions are clearly associated with two straight lines comprising different power-laws. However, it is difficult to determine the single power-law in the recent node strength distributions since the fluctuation in the tail has to be verified with a statistical tolerance. To convincingly determine the knowledge structure, we need to evaluate the estimated node strength distribution with the goodness-of-fit measure.

The evolution of core/periphery structures can be seen via the estimated results for LCD and PDP tabularized in Table 1 and Table 2, respectively. The breakpoint designates the transition point of the two-tiered structure in the node strength distribution. Results for each linear regression in the core and periphery are also described. In the goodness-of-fit column, the discrepancy between the empirical data and the sample distribution is quantified for the entire distributions because the

Table 2
PDP core/periphery structure estimation.

Period	Break-point	Periphery				Core				Goodness of fit	
		Exponent[a]	Std error	*t*-stat	*p*-value[†]	Exponent[a]	Std error	*t*-stat	*p*-value[†]	KS test	*p*-value[‡]
1982–1997	7.12	1.29	0.12	−2.4	0.0256	3.03	0.18	−10.97	<0.0001	0.58	0.8928
1982–1998	7.44	1.29	0.06	−5.06	< .0001	2.79	0.08	−22.09	<0.0001	0.36	0.9995
1982–1999	7.19	1.26	0.07	−3.95	0.0003	2.54	0.09	−17.91	<0.0001	0.44	0.9912
1982–2000	6.51	1.26	0.06	−4.03	0.0002	2.41	0.08	−16.94	<0.0001	0.44	0.9912
1982–2001	7.58	1.39	0.09	−4.32	0.0001	2.51	0.12	−12.63	<0.0001	0.43	0.9923
1982–2002	7.58	1.47	0.1	−4.78	<0.0001	2.4	0.13	−10.92	<0.0001	0.32	0.9999
1982–2003	8.14	1.58	0.07	−7.44	<0.0001	2.3	0.1	−12.66	<0.0001	0.32	0.9999
1982–2004	8.52	1.64	0.06	−11.32	<0.0001	2.24	0.07	−16.66	<0.0001	0.31	1.0
1982–2005	7.15	1.67	0.05	−16.02	<0.0001	1.99	0.06	−13.37	<0.0001	0.29	1.0
1982–2006	5.39	1.59	0.07	−8.76	<0.0001	1.96	0.08	−12.42	<0.0001	0.28	1.0
1982–2007	3.45	1.35	0.08	−4.32	<0.0001	2.07	0.09	−12.18	<0.0001	0.27	1.0
1982–2008	3.33	1.37	0.09	−4.29	<0.0001	2.02	0.09	−11.01	<0.0001	0.26	1.0
1982–2009	3.05	1.38	0.11	−3.35	0.0014	1.95	0.12	−8	<0.0001	0.35	0.9997
1982–2010	2.5	1.2	0.16	−1.28	0.2049	2.09	0.16	−6.73	<0.0001	0.33	0.9999
1982–2011	2.46	1.2	0.16	−1.27	0.2065	2.08	0.16	−6.53	<0.0001	0.32	0.9999

[a] Values are estimated exponent + 1 to compensate for decrease in linear regression on complementary cumulative distribution functions (CCDFs).
[†] *p*-values are produced by Student's *t*-test for a log-linear regression.
[‡] *p*-values are produced by Kolmogorov–Smirnov (KS) test.



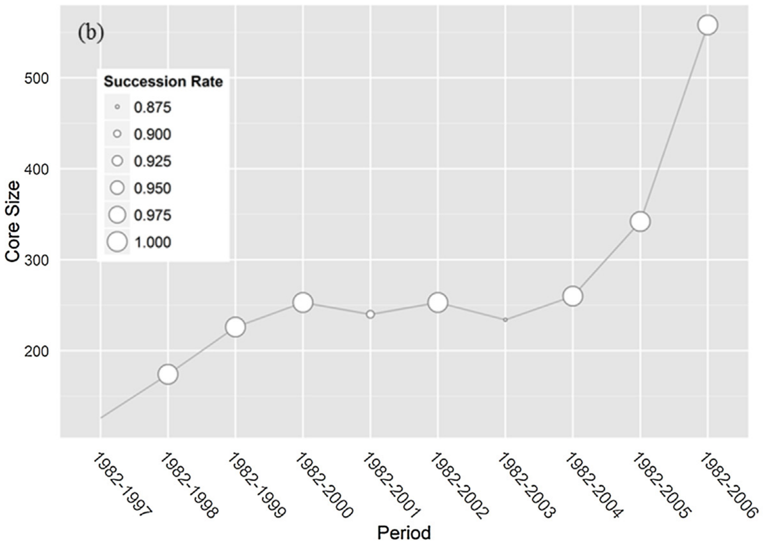


Fig. 5. Number of core keywords for (a) LCD and (b) PDP and succession rate: Each point in the plots represents the number of keywords in the core, and its size is proportional to the succession rate, which implies the keyword overlapping rate compared to the previous period on the core networks.

p-values measured from *t*-statistics of each realm are not persuasive enough for the whole system. The *p*-value from the KS test is tend to one, there are higher possibilities corresponding to a fit.

First of all, it should be determined whether the distribution is the core/periphery structure or not. Based on the KS test, we can conclude that the estimation is statistically significant, but exponents in the early periods are unsettled. Table 1 indicate that the core keywords of LCD technology were initially formed in 1994. In this regard, Lin (2012) noted that the first technology cycle in the LCD industry appeared in 1995. We thus find that scholars and industries started to develop round the same time as regards LCDs. Furthermore, breakpoints connote another result. For PDP technology, after 2007, the breakpoint is set below node strength four. Therefore, even though LCD technology still has the core/periphery structure, PDP technology shows a single power-law distributions after 2007. This result would be related to the fact that the size advantage for PDPs did not last long as 32 inch LCD models became widely available by 2004. Following the design competition, the FPD industry competed for refinements and economies of scale. The unit cost of production is a vital part of success in the market and LCDs achieved economies of scale. As if forecasts have been realized (DisplaySearch, 2010; Kreng and Wang, 2009), the market size of LCDs predominates that of PDPs. Previous studies considered LCD to be a leading technology (Gnyawali and Park, 2011) and PDP to be a shrinking technology (Na et al., 2011) in the FPD field.

We can observe the expansion and contraction of the core through the change in the breakpoint and core sizes in Fig. 5. We can also find the succession rate of the core in Fig. 5. The core is almost piled up on the core keywords in the previous period. This high repetition rate supports well-known theories such as the incremental development in cyclical

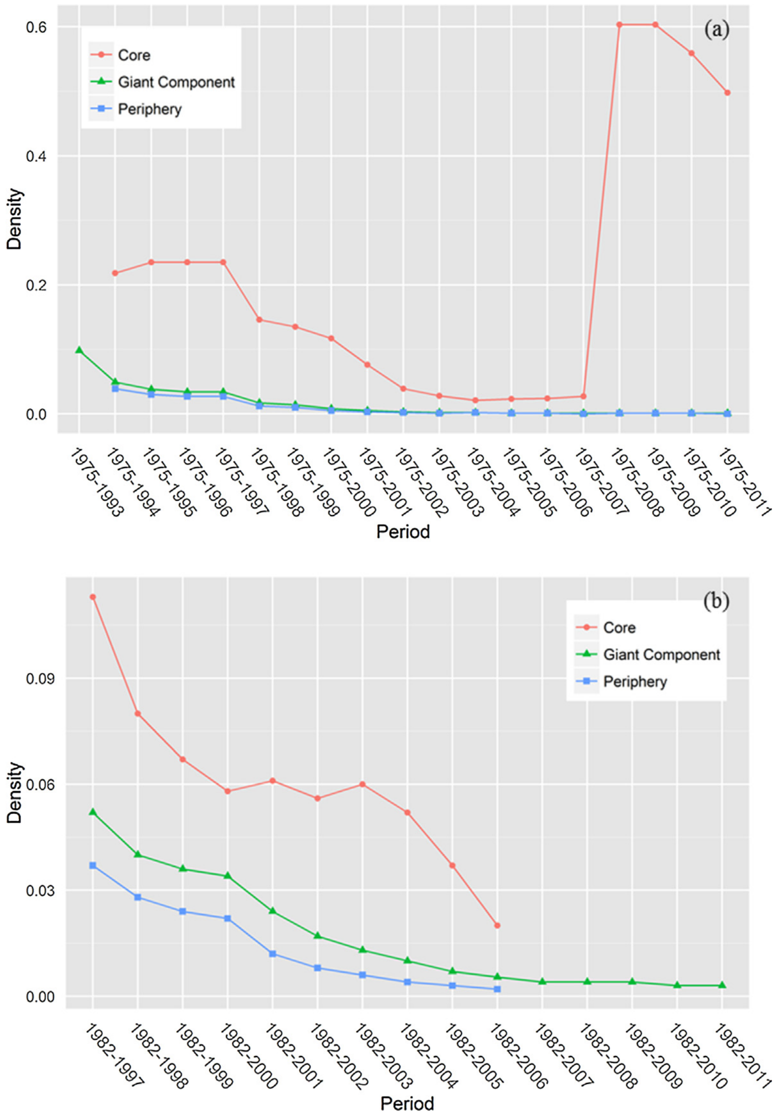


Fig. 6. Density for (a) LCD and (b) PDP: "Core" and "Periphery" denote the core network and the periphery network; "Giant Component" signifies the largest component in the whole network.

development of technologies (Anderson and Tushman, 1990), the puzzle-solving process in Kuhn's paradigm shift (Kuhn, 1996), and the engineering as problem solving in the evolution of technology (Arthur, 2009).

As the core/periphery structures are transformed, other network properties also change. Fig. 6 shows the transition of density in the core, the periphery, and the giant component. Here, the giant component, the largest component of the original network, is compared with realms in the dichotomous structure because all nodes in the giant component are guaranteed to be connected in contrast to the original network composed of various disconnected sub-networks. The density in two-tiered power-law distributions is measured in the same order: core, giant component, and periphery. The core retains the structure that is most stable to perturbations. As the core enlarges, the cohesiveness between core keywords becomes weaker. The densities converge upon the density in the giant component, with the exception of the period from 2006 in LCD, when the core is readjusted to a small scale. Subsequently, there is another downward trend in the density of LCDs from 2006.

The estimated exponents give information about an imbalance of research intensity between the core and peripheral components. Fig. 7 delineates the change in exponent with a 95% confidence interval and both exponents are considered to be statistically unequal. A greater exponent means that the research theme tends to concentrate more on a small number of keywords. Most of the cores have a greater exponent than the peripheries. Intensive research was conducted around keywords in the core until after the mid-2000s. The LCD research intensity reversed starting at 2006. Regarding the abrupt

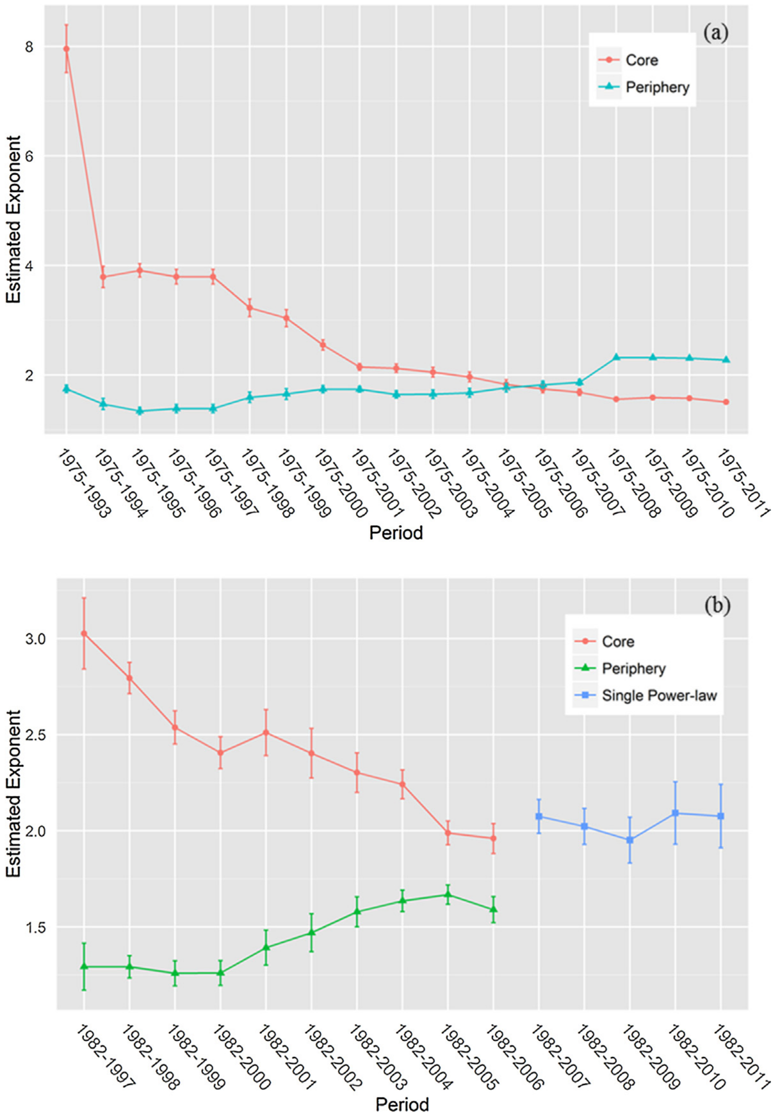


Fig. 7. Power-law exponent and 95% confidence interval for (a) LCD and (b) PDP.

changes in industrial development, Lin (2012) pointed out that global recession in mid-2000s contributed to the breaking of the developmental cycle in the LCD industry.

An interesting result in the LCD case is that the exponents in the core/periphery are reversed and the core area condenses starting from 2006. The new core regime is settled and research on LCD is more concentrated in the peripheral keywords than the cores. Various explanations can be proffered: This discontinuity may suggest the opening of a new technological regime; namely, the opening of the second generation of LCD technology (Anderson and Tushman, 1990). Further, a decreasing core size may lead to development bottlenecks, or may reduce the flexibility of the whole system. However, a smaller core with tighter controllability of the network may allow easy transformation (Csermely et al., 2013). Nevertheless, it is too early to eliminate the possibility that residual effects remain due to excessive concentration of hot topics such as active matrices, backlights, and TFTs. If the residual effects are influenced, the node strength will have a single power-law distribution in the near future.

5. Conclusions

Evolutionary theories for technological and scientific change resemble each other in the stable knowledge base-related developmental patterns. The emergence of stable knowledge bases triggers developmental pattern changes from variational to incremental progress. Scholars interpreted the emergence of stable knowledge as the core formation in the core/periphery structure. Robustness, which these segregated structures possess, is also known to be a suitable characteristic for evolution. Once core components are formed, subsequent development emphasizes expansion of the core area. However, the well formulated theories about technological and scientific evolutions require empirical validation.

As a means of providing empirical confirmation, this paper analyzed scientific progress from the perspective of a complex network. Specifically, we investigated the evolution of a keyword co-occurrence network based on the core/periphery structure. To detect the core/periphery dichotomy, we investigated the two-tiered power-law behavior of node strength. Structural properties, such as density and the number of nodes, were exploited to elucidate the evolution of the core/periphery dichotomy. As an illustration, we delineate the development of technological rivalry in Flat Panel Displays (FPDs): LCD vs. PDP. Even the base principles, LCD and PDP adopt, are distinct, they have a common purpose for electronic visual displays. Moreover, both technologies emerged as core/periphery structures in the initial stage of scientific growth. According to the theories in scientific development, after formation of core realm, we can expect that the nature of competition takes on new aspects from variations to incremental improvements. However, this study ends with the indecisive explanation for the evolution of the dichotomous structure due to short data history to determine whether drastic changes of LCD between 2007 and 2008 mean a newly-formed core or just artifacts.

The core/periphery structure in the keyword network is an effective method to trace the structural evolution of the scholar community. In spite of the formal evolutionary models of scientific diffusion, each scientific trajectory generates different patterns of development (Cunningham and Kwakkel, 2014). This paper showed an empirical evidence of a scientific trajectory, using a method that can be applied to other technological cases. To be convinced of the developmental trajectories, in particular, we need to analyze several networks, such as FPDs and other sub-technologies, with various detection methods of the core/periphery structure like the rich-club (Colizza et al., 2006), the k-core decomposition (Liu et al., 2014), and the knotty centrality (Shanahan and Wildie, 2012). The structural changes to keyword networks from multiple levels would help to explicate scientific cycles on complex systems. Even this study tenuously deals with structural features of network dichotomy, we think it is worthwhile exploring the issue further for the future study, such as the robust characteristics of the core. To accomplish that, we are going to investigate the effect of perturbations on the core by using network modeling in a sequel. Finally, we believe that common features derived from accumulated evidences can provide insights into scientific evolution

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