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Quantitative mapping of patented technology — The case of electrical conducting polymer nanocomposite

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ABSTRACT

This study aims to obtain global technology evolution by constructing and analyzing patent citation network and patent citation map for the field of electrical conducting polymer nanocomposite. A total of 1421 patents are retrieved from USPTO patent database and patent citation network is established by combing both patent citation and social network analysis. Network properties, e.g. Degree Centrality, Betweenness Centrality, and Closeness Centrality, are calculated for representing several technology evolution mechanisms that first proposed in this study. Also, a distance-based patent citation map is constructed by calculating relative distances and positions of patents in the patent citation network. Quantitative ways of exploring technology evolution are investigated in this study to unveil important or emerging techniques as well as to demonstrate dynamics and visualization of technology evolutions.

1. Introduction

1.1. Mapping knowledge evolution by bibliometric analysis

Kuhn published "The structure of scientific revolution" [1] and popularized the terms "paradigm" and "paradigm shift". Dosi [2] investigated technology trajectory on the basis of paradigm shift and found continuous innovation can be regarded as proceedings of technology paradigm, while discontinuous innovation might be the initiation of a new paradigm. The differentiation between continuous innovation and discontinuous innovation may be positive for understanding initiation of a new paradigm as well as position and diffusion of a specific technology or knowledge. A lot of methodologies have been proposed and applied into various knowledge fields for understanding or mapping their technology development paradigms. However, what usually used for this purpose is bibliometric analysis on patents or scientific papers by way of text mining and statistics, keyword-based approach or citation-based approach.

Kostoff has very complete and systematic studies on literature-related analysis and publishes a series of papers based on combination of text mining and statistics on scientific papers, also he proposes a systematic Literature-related discovery method for linking two or more literature concepts that have heretofore not been linked, in order to produce novel, interesting, plausible, and intelligible knowledge [3–19].

Attempts have been made to explore ways of mapping knowledge evolution. Keyword-based analysis as a type of co-word analysis [20,21]started to play an important role in understanding the dynamics of knowledge development [22]. Ding et al.

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mapped information retrieval research by using co-word analysis on papers collected from Science Citation Index (SCI) and Social Science Citation Index (SSCI) for the period 1987–1997 [23]. Baldwin et al. mapped ethics and dementia research by using keywords [24]. Tian et al. used Institute for Scientific Information (ISI) database to measure scientific output of the field of Geographic Information System (GIS) by using keywords [25]. Similar approaches have been made to map knowledge evolution in other fields, such as software engineering [26], chemistry [27], scientometrics [28], neural network research [29,30], biological safety [31], optomechatronics [32], bioeletronics [33], adverse drug reactions [34,35], biotechnology [36,37], environmental science [38], condensed matter physics [39], etc., and even this keyword-based analysis has been applied to investigation of a phenomenon or a more specific topic such as severe acute respiratory syndrome (SARS) and tsunami [40,41], and Parkinson's disease [42].

However, the above mentioned methodologies are all based on keyword analysis which provides less sense of knowledge accumulation over time or limited understanding on causal interpretation of human knowledge development. Therefore, citation-based analyses have been also widely investigated by researchers to avoid the above mentioned problem and facilitate bibliometric analysis on accumulated knowledge. For example, Kajikawa has utilized citation analysis on SCI papers together with clustering citation network actors to understand structural change of sustainable energy [43], biomass and bio-fuels [44] and organic LED [45].

1.2. Mapping patented technology by patent citation

It has long been a very critical part of human knowledge system that patent and scientific publications are two most significant ways of disclosing science and technology progress in the society. Former publications can be served as important references or bases for later publication, in this way human knowledge can be gradually accumulated to sustain and expand knowledge system. The important featuring characteristic of patent and scientific publication for knowledge accumulation is their citations showing which former literatures have been contributed to this paper/patent and providing the context of knowledge accumulation. A number of researches have noted that patent citations trace out technological building relationships among inventions [46,47]. Also, citation has been widely used in bibliometric study to evaluate technology development, research performance, and even map knowledge evolution or technological trajectory. For instance, Acosta investigated the links between science and technology based on an analysis of scientific citations in patent documents to study in greater depth the relationship between science and technological development in the various regions of Spain [48], Hall et al. suggested that of all patent related indicators, patent citation is a more adequate indicator to evaluate market value [49], Stuart and Podolny used patent citations to measure firms' technological niches and niche shifts [50].

Otte and Rousseau studied citation network, utilized as a type of social interaction networks, by the use of social network analysis, and calculate network property to discover how information can be disseminated among actors [51], and Liebowitz indicated the possibility of mapping knowledge flows and measuring relationships among actors in a network [52]. Accordingly, this study aims to use the alternative citation-based method to avoid the problem of lacking causal knowledge accumulation if only keywords are considered in the analysis, and reap reward from the well-assigned citations in structured patent documents for drawing an overview of how electrical conducting polymer nanocomposite technology is evolved. In summary, patent citation information allows the building of patent linkages which eventually lead to a patent citation network as a whole. The constructed patent citation network, with patents as network nodes (actors) and patent citation as network ties, allows quantitative analysis on patent citation network by calculating network properties, e.g. Degree Centrality, Betweenness Centrality, and Closeness Centrality. In this sense, mechanism of knowledge flow or technology evolution mechanism, e.g. technology convergence, technology diffusion, etc., can be quantitatively analyzed.

However, a lot of similar attempts have been made to obtain technology development contexts by patent citation analysis [43–45,47], the purpose of this study is not to use conventional method to investigate a new technology domain, but to extend from conventional patent citation network research to a more systematic process of patented technology evaluation together with converting 3-dimensional citation network to a 2-dimensional patent map which can be more easily interpreted by human eyes. The quantitative 2-dimensional map provides a quick way, which is much easier than complex equations or theories, for people to directly perceive technological change through human eyes.

2. Research method

2.1. Initial patent sampling

This research selects nanocomposite material as research target to draw its patent citation network. Patents with “nano” and “composite” appeared in title or abstract of patents are retrieved from USPTO (Patent retrieval time: Jun. 11, 2008). The retrieved patents are carefully reviewed to remove those which are not closely related to nanocomposite material, and finally a total of 672 patents are remained as “initial patent” in this study.

2.2. The development of technology–function matrix

The obtained 672 patents are critically analyzed and classified into two dimensions: 1) technological dimension based on the matrix material disclosed in patents, i.e. Polymer, Clay, Ceramic, Metal, etc., and 2) functional dimension based on the function of invented techniques, i.e. Mechanical and dimensional stability, Permeability, Thermal stability, Flame retardancy, Chemical resistance, Surface appearance, Electrical conductivity, Optical and light emitting property, Cement/adhesivity, Magnetic property, etc. (Table 1). Validation is done by comparing the content of classified patents with multiple sources and through informal interviews with members of the expert panel. It is worth noted that one single patent may disclose more than one matrix material or more than one

Table 1
Initial 672 patents classification on the basis of material and functions.

		Matrix material					
		Polymer	Clay	Ceramic	Metal	Other	Total
Function	Mechanical and dimensional stability	176	4	59	35	11	285
	Permeability	52	1	1	0	1	55
	Thermal stability	70	1	16	13	3	103
	Flame retardancy	19	0	0	0	1	20
	Chemical resistance	17	0	5	4	4	30
	Surface appearance	6	0	2	0	1	9
	Electrical conductivity	69 [a]	0	28	30	21	148
	Optical and light emitting property	77	0	19	10	15	121
	Cement/adhesivity	7	0	1	0	0	8
	Magnetic property	10	0	7	28	0	45
	Other	56	2	20	19	23	120
	Total	503	6	138	120	57	824

[a] Research target selected in this study.

function, one patent thus can be categorized into more than one classification, so the total patent count in Table 1 is 824 instead of the original 672. The classification of "other" in both matrix and function in Table 1 are either some other materials or functions not considered in this study, or more than three matrices or functions are disclosed in one single patent trying to reduce the specificity of its disclosed matrix or function. The obtained technology–function matrix shown in Table 1 provides an overview, or a so-called "patent map", for the development of nanocomposite material. Subsequently, this research selects 69 patents with the technology of "polymer" matrix and function of "electrical conductivity" to meet the requirement of the research target set in this study.

2.3. Network patent sampling

After classification of technology and function, the 69 patents with polymer matrix and function of electrical conductivity are used as primary patents based on which their backward citation patents and forward citation patents are retrieved from USPTO database as the secondary patents which are upstream patents and downstream patents of the primary patents, respectively. By examining upstream and downstream patents, a technological context of what upstream patents contribute to primary patents and what downstream patents are contributed by primary patents can be understood and the underlying knowledge flows can thus be analyzed. In summary, this research uses 1) primary patents: the 69 patents with polymer matrix and function of electrical conductivity, and 2) secondary patents: 690 backward citation patents of the 69 primary patents and 716 forward citation patents of the 69 primary patents, as actors of the patent citation network to be drawn in this study. The total number of obtained patents is 1421 instead of 1475 (the sum of primary patents and secondary patents) after removal of duplicated count (some patents belong to both primary and secondary patents). The 1421 patents are defined as "network patents" and are therefore treated as network actors (node), along with the network ties built by patent citation linkages, a patent citation network for understanding the development context of electrical conducting polymer nanocomposite can be achieved.

2.4. Patent citation network and network property calculation

After construction of the patent citation network, network property is subsequently calculated. In social network theory, "Centrality" is a key network property to estimate how easy an actor retrieves or controls resources from the network. Freeman proposed three ways of measuring network centrality, Degree Centrality, Betweenness Centrality, and Closeness Centrality [53]. The higher centrality indicates more associations with actors in a network. Brass and Burkhardt [54] pointed out the higher centrality of a person in a social network, the more power s/he possesses from the viewpoint of organizational behavior. This research also uses the three ways of measurement for obtaining centrality of patented technology in order to understand the importance, influence, diffusivity and convergency of a patented technology.

2.4.1. Degree Centrality

Network nodes (actor) which directly linked to a specific node are in the neighborhood of that specific node. The number of neighbors is defined as nodal degree, or degree of connection. Granovetter suggested nodal degree is proportional to probability of obtaining resource [55]. Nodal degree represents to what degree a node (actor) participates the network, this is a basic concept for measuring centrality.

InDegree Centrality: the number of time that patent i is cited by other patents. The higher InDegree Centrality, the more times that patent i is cited, meaning the higher momentum of knowledge diffusion from patent i to other patents.

$$d(i) = \sum_j m_{ji}$$

$m_{ji} = 1$ if patent i is cited by patent j.

OutDegree Centrality: the number of times that patent *i* cites other patents. The higher OutDegree Centrality, the more times that patent *i* cites other patents, meaning the higher momentum of knowledge convergence from other patents to patent *i*.

$$d(i) = \sum_j m_{ij}$$

$m_{ij} = 1$ if patent *i* cites patent j.

2.4.2. Betweenness Centrality

The concept of betweenness is a measure of how often an actor is located on the shortest path (geodesic) between other actors in the network. Those actors located on the shortest path between other actors are playing roles of intermediary that help any two actors without direct contact reach each other indirectly. Actors with higher Betweenness Centrality are those located at the core of the network.

$$b(i) = \sum_{j,k \neq 1} \frac{g_{jik}}{g_{jk}}$$

g_{jk} : the shortest path between patent (actor) *j* and patent *k*.
g_{jik} : the shortest path between patent *j* and patent *k* that contains patent *i*.

2.4.3. Closeness Centrality

The Closeness Centrality of an actor is defined by the inverse of the average length of the shortest paths to/from all the other actors in the network. Higher Closeness Centrality indicates higher influence on other actors. In a directed network, Closeness Centrality can be divided into InClosenesss Centrality and OutCloseness Centrality.

InCloseness Centrality: the shortest path from other patents to patent *i*, the higher InCloseness Centrality, the higher influence of patent *i* on other patents.

$$c(i) = \sum_{j=1}^{N} \frac{1}{d_{ji}}$$

d_{ji}:the shortest path from patent *j* to patent *i*.

OutCloseness Centrality: the shortest path from patent *i* to other patents, the higher OutCloseness Centrality, the easier for patent *i* to be influenced by other patents.

$$c(i) = \sum_{j=1}^{N} \frac{1}{d_{ij}}$$

d_{ij}:the shortest path from patent *i* to patent *j*.

2.5. Concordance between network properties and technology evolution mechanisms

The previously mentioned network properties can be used as indicators for characterizing technology evolution context, and therefore quantitative analysis on the evolution context can be obtained. In this study, we propose the applications of the five network properties on evaluating evolution contexts for electrical conducting nanocomposite technology, namely the concordance between network properties and technology evolution mechanisms, which provides a quantitative approach toward evolution mechanism:

(1) InDegree Centrality: the number of times that a patent is cited, it can be used as an indicator to measure knowledge flow from one target patent to later patents. Because of its implication of knowledge diffusion, InDegree Centrality is defined as an indicator to measure momentum of technology diffusion.
(2) OutDegree Centrality: the number of times that a patent cites other patent(s), it can be used as an indicator to measure knowledge flow received by a target patent. Because of its implication of knowledge convergence, OutDegree Centrality is defined as an indicator to measure momentum of technology convergence.
(3) Betweenness Centrality: how often an actor is located on the shortest path (geodesic) between other actors in the network. Therefore, Betweenness is defined as an indicator to measure momentum of technology transition.
(4) InCloseness Centrality: the shortest path from other patent(s) to a target patent. The shorter path, the stronger the target patent influences other patent(s). InCloseness Centrality is therefore defined as an indicator to measure momentum of influence.
(5) OutCloseness Centrality: the shortest path from a target patent to other patent(s). The shorter path, the stronger the target patent is influenced by other patent(s). OutCloseness Centrality is therefore defined as an indicator to measure momentum of being influenced.

Even though the five network properties represents five mechanisms of technology evolution. Patents with higher centralities are those located closer to the core of a target research field, or they can be called the core patents. But the idea of “core” relies on which of the five above indicators is used.

2.6. Constructing distance-based patent citation map

In this study, a patent citation map is obtained by calculating relative positions and density of network actors in a two-dimension map on the basis of network constructed previously. We use algorithm proposed by van Eck and Waltman's in 2007 [35].

1) Actor position: the positions of network actors in the map are based on visualization of similarities. If there are totally n actors, a two-dimensional map where the actor 1–n are positioned in a way that the distance between any pair of actor i and j reflects their association strengths a_{ij} as accurately as possible, i.e. distance between i and j is proportional to a_{ij}, van Eck and Waltman's algorithm is used to minimize a weighted sum of the squared Euclidean distance between all pairs of actors, the objective function to be minimized is given as below:

$$E(x_1, \ldots, x_n) = \sum_{i<j} a_{ij} \left\| x_i - x_j \right\|^2$$

Where the vector $x_i = (x_{i1}, x_{i2})$ denotes the location of actor i in a two-dimensional space and ||•|| denotes the Euclidean norm.

2) Actor density: actor density at a specific location in a map has to be calculated. The actor density is calculated by first placing a kernel function at each actor location and taking a weighted average of the kernel function.

The actor density at location $x = (x_1, x_2)$ is given by

$$D(x) = \frac{1}{h^2 \sum_{i=1}^{n} c_{ii}} \sum_{i=1} c_{ii} K\left(\frac{x_1 - x_{i1}}{h}, \frac{x_2 - x_{i2}}{h}\right)$$

Where K denotes a kernel function and h denotes a smoothing parameter. C_{ii} denotes the number of occurrence of actor I and $x = (x_1, x_2)$ denotes the location of actor i in the map. The kernel function K is a non-increasing Gaussian kernel function given by

$$K(t_1, t_{2n}) = \frac{1}{2\pi} exp\left(- \frac{t_1^2 + t_2^2}{2} \right)$$

3. Results and discussion

The selection of paper or patent used for discovering development trend will fundamentally lead to different results. The relation between paper and patent has long been subject to debate. However, instead of analyzing the interplay between paper and patent, this study aims to shed light on the use of patent as a technological system for understanding technological trends as well as propose a systematic and quantitative method for the patent-based mapping.

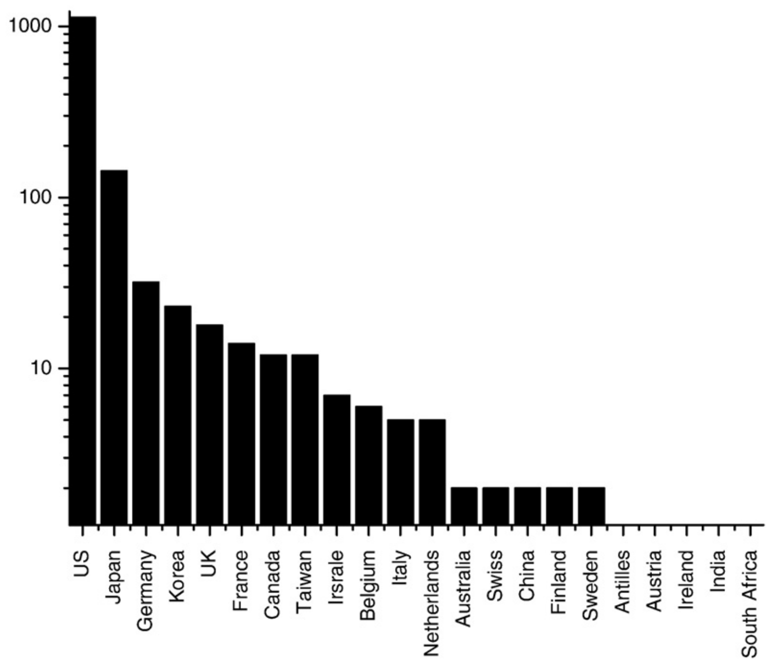

Fig. 1. Patent count by countries.

Table 2
Top 20 standard industrial classifications for 1069 network patent.

Ranking	Standard Industrial Classification (SIC)	SIC code	Patent count
1	Electronic components and accessories and communications equipment	366–367	213
2	Professional and scientific instruments	38 (except 3825)	197
3	Rubber and miscellaneous plastics products	30	122
4	Industrial inorganic chemistry	281	112
5	Miscellaneous chemical products	289	105
6	Paints, varnishes, lacquers, enamels, and allied products	285	95
7	Plastics materials and synthetic resins	282	80
8	Electrical industrial apparatus	362	62
9	Industrial organic chemistry	286	41
10	Stone, clay, glass and concrete products	32	37
11	Textile mill products	22	36
12	Miscellaneous electrical machinery, equipment and supplies	369	33
13	Special industry machinery, except metal working	355	26
14	General industrial machinery and equipment	356	23
15	All other SICs	99	16
16	Electrical lighting and wiring equipment	364	15
17	Fabricated metal products	34 (except 3462, 3463, and 348)	14
18	Drugs and medicines	283	9
19	Primary and secondary non-ferrous metals	333–336, 339 (except 3399), and 3463	9
20	Agricultural chemicals	287	8

Data source: this study, (USPTO UPC to SIC concordance, 2008).

3.1. Initial patent analysis

According to the technology and function matrix shown in Table 1, in terms of technology, most patents disclosed nanocomposite material with polymer matrix (503 patents) and subsequently ceramic matrix (138 patents). In terms of function, most patents are for

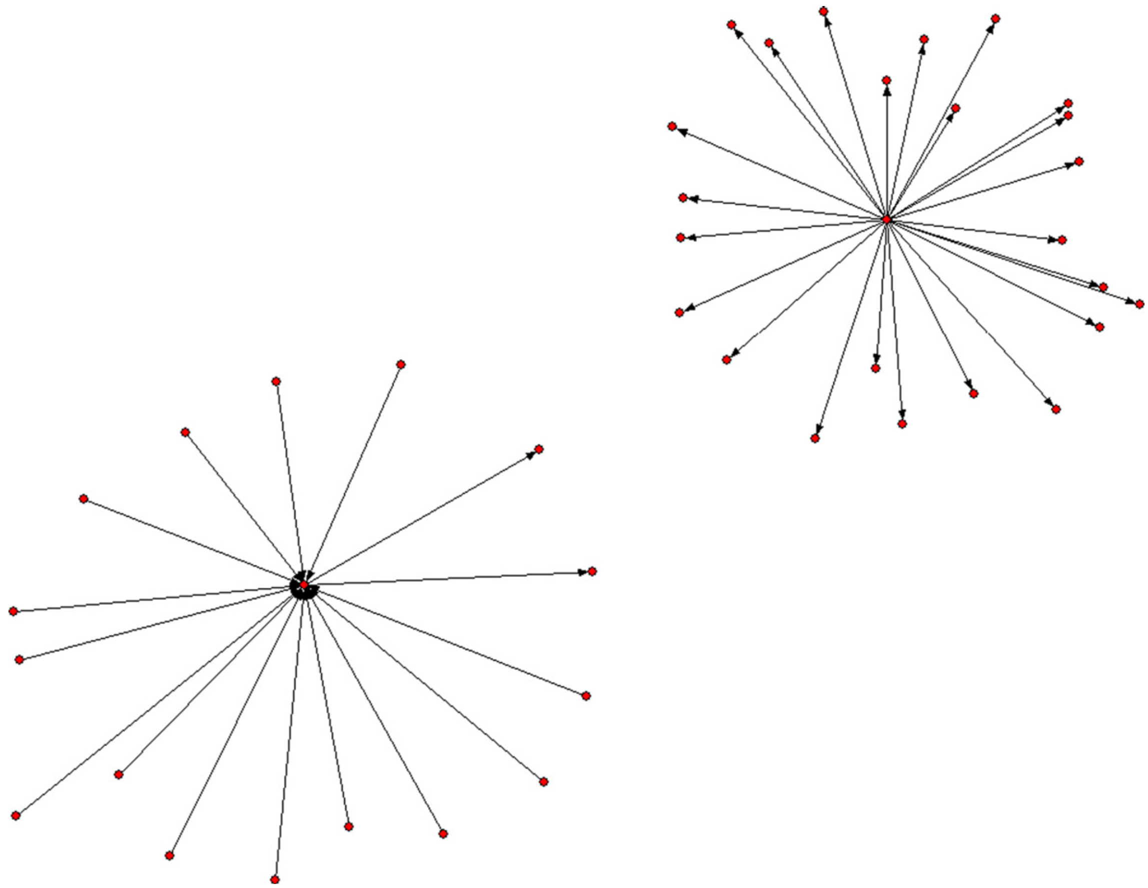

Fig. 2. Patent citation network for electrical conducting polymer nanocomposite for 1952–1991.

mechanical and dimensional stability (285 patents), and then electrical conductivity (148 patents), and optical and light emitting property (121 patents). This research aims to study electrical conducting polymer nanocomposite, so the 69 patents with technology of "polymer" matrix and function of "electrical conductivity" are selected as primary patents for subsequent investigation.

3.2. Network patent analysis

For all the obtained 1421 network patents, countries with the most patents are US (1129 patents), Japan (143 patents), Germany (32 patents), Korea (23 patents), and UK (18 patents). This reveals that electrical conducting polymer nanocomposite related technologies are mainly located in the US, Japan, and Europe but US is much more significant than other countries (Fig. 1).

If 1421 network patents are classified by Standard Industrial Classification) (USPTO UPC to SIC concordance, 2008) [56], as shown in Table 2, there are 213 patents in no. 1 classification (electronic components and accessories and communications equipment), 197 patents in no. 2 classification (professional and scientific instruments), and 122 patents in no. 3 classification (rubber and miscellaneous plastics products). The sum of classification no. 1, 2 and 3 is more than one third of the total 1421 network patents. This implies the strong application of electrical conducting polymer nanocomposite on electric instrument, and the emerging nanotechnology combined with conventional nanocomposite material bring great influences on electronic components or scientific instrument.

3.3. Patent citation network analysis

3.3.1. Network visualization

The patent citation network composed of 1421 patents and 1705 patent citation relationships are plotted by computer, shown in Figs. 2–4 for patents filed on different time period (note: patents which act as isolated node/actors without any networking are

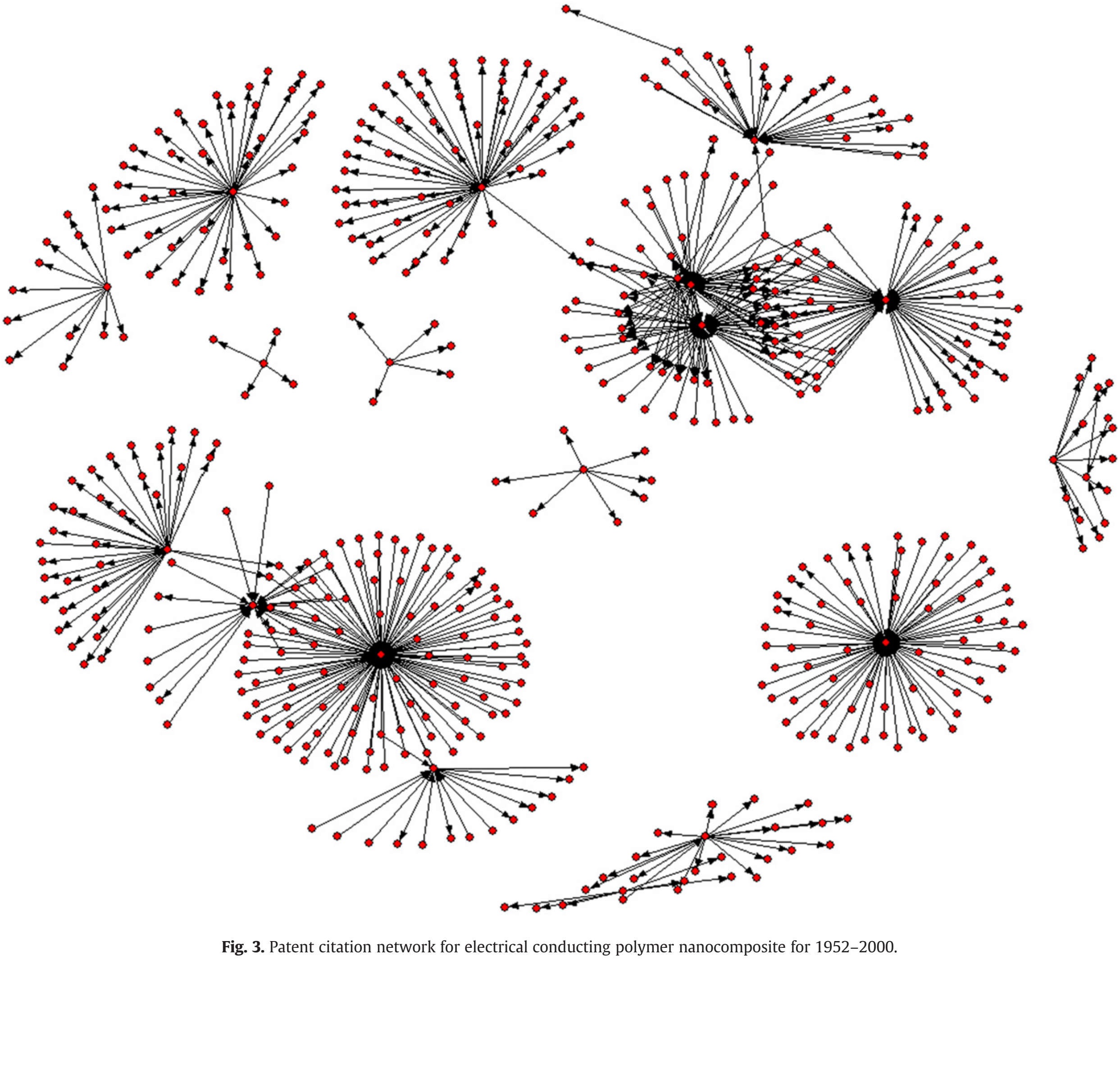

Fig. 3. Patent citation network for electrical conducting polymer nanocomposite for 1952–2000.

not shown in figures). Each node represents a patent and each network tie with arrow represents a citation relationship. The patents pointed by arrows of the network ties are cited by those located at the other end of the network ties. In Fig. 2, patent citation network based on patents filed in the period 1952–1991 is plotted and only several patents are networked together and presented a simple radial structure. In Fig. 3, more patents are networked for the period 1952–2000 but still several separated clusters can be observed. In Fig. 4, networking is fully matured and almost all patents are networked together for the total time period 1952–2008 in this study.

3.3.2. Network properties calculation

According to aforementioned method of calculating network properties, network properties, i.e. Betweenness Centrality, InCloseness Centrality, OutCloseness Centrality, InDegree Centrality and OutDegree Centrality of each network node are calculated. Fig. 5 shows the average of Betweenness Centrality, OutDegree Centrality and InDegree Centrality for each year. Significant peaks around the period of 1984 and 1992, 1997–2001 indicate important time periods for development of related technology. After 1992, network becomes more mature. The similar peak positions for Between Centrality curve and InDegree Centrality curve suggests technology diffusion and technology transition are closely associated with each other.

Network properties (InDegree Centrality, OutDegree Centrality, and Betweenness Centrality) for each country are also averaged to determine how significant a country contributes to the development of technology. As shown in Fig. 6, US, Taiwan, and Korea are the three countries with the highest Betweenness Centralities. Antilles, Ireland, and US are the three countries with the top three InDegree Centralities, and Israel, Canada, and Korea are the three countries with the top three OutDegree Centralities. However, since each country possesses different number of patents, statistical bias for countries with limited number of patents is possible.

Table 3 shows patents with top 10 network properties. These patents with top network properties are core patents or key technologies that are classified by aforementioned momentums of technology development, i.e. technology diffusion, technology

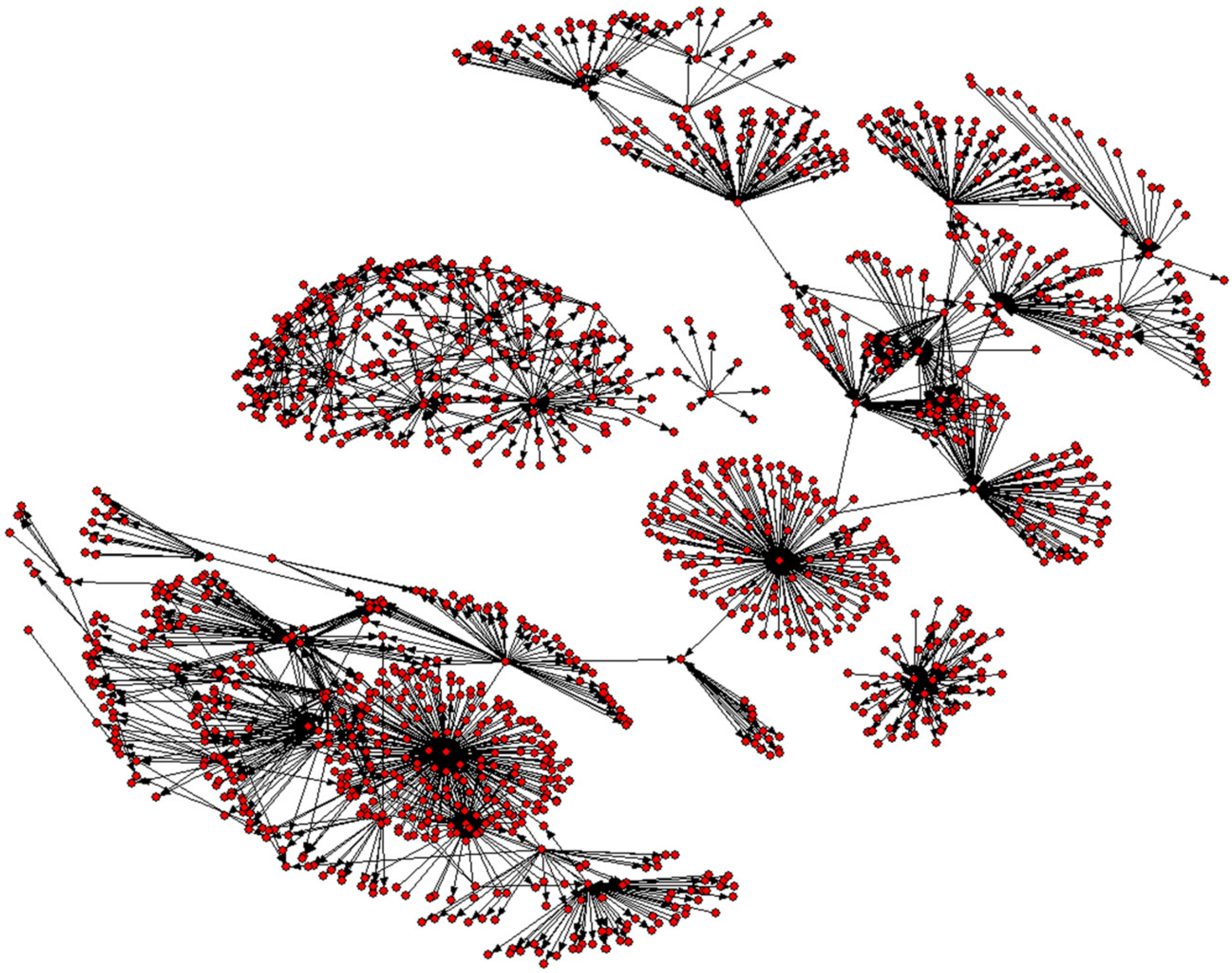

Fig. 4. Patent citation network for electrical conducting polymer nanocomposite for 1952–2008.

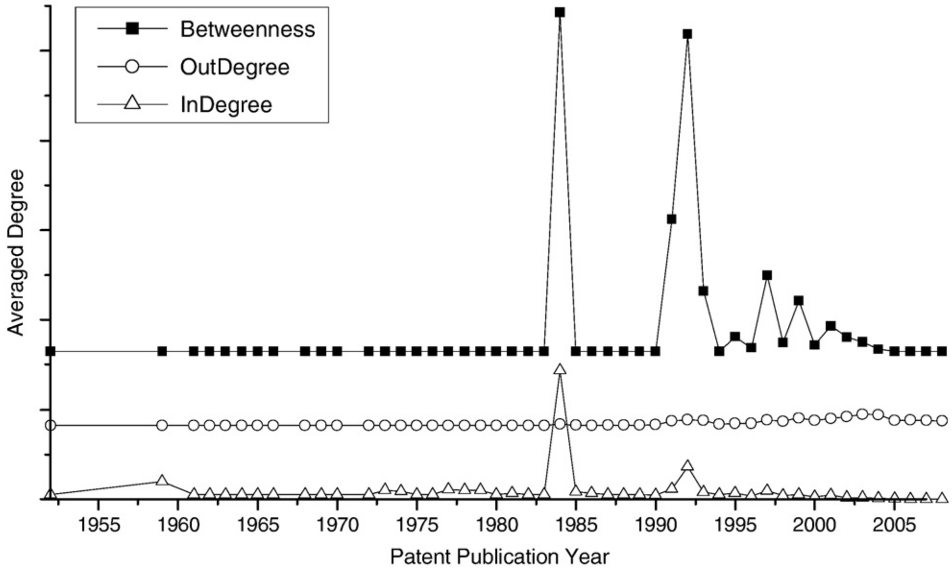

Fig. 5. Average of Betweenness Centrality, Outdegree Centrality and InDegree Centrality for each year.

convergence, influence, being influenced, and technology transition. Patents listed in Table 3 are completely filed by the US assignees. Endicott Interconnect Technologies, Zyvex Performance Materials, Minnesota Mining and Manufacturing Co., and Hyperion Catalysis International are top companies that own most patents in Table 3, indicating their important roles as core actors in this technology field.

3.3.3. 2-dimensional mapping

The patent citation map with country as actor is shown in Fig. 7 (Color gradient from blue to red indicates low to high actor density) where two separate domains reflecting distribution pattern of global techniques. The two domains dominated by the two countries with highest number of patents— the US and Japan. Where the US can be seen as the technology leader of countries of Belgium, Netherlands, Sweden, South Africa, Austria, China, Netherlands Antilles, Australia, India, Switzerland, and Ireland. On the

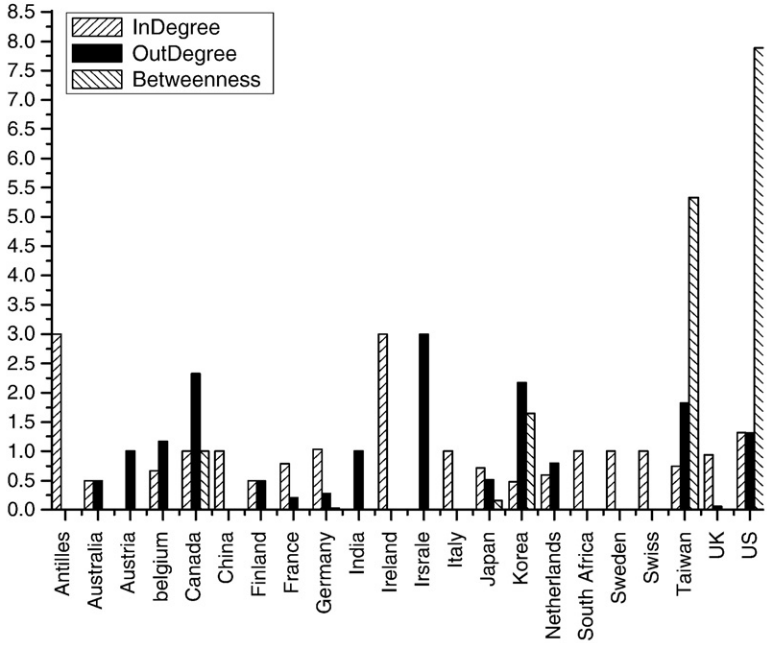

Fig. 6. InDegree Centrality, Outdegree Centrality, Betweenness Centrality for each country.

Table 3
Patents with top 10 network properties

Ranking	InDegree Centrality — momentum of technology diffusion Patent no.	OutDegree Centrality — momentum of technology convergence Patent no.	InCloseness Centrality — momentum of influence Patent no.	OutCloseness Centrality — momentum of being influenced Patent no.	Betweenness Centrality — momentum of technology transition Patent no.
1	4663230	7217754	7025607	7025607	5338430
2	5278020	6616794	7235745	7235745	5278020
3	5589152	7265174	7384856	7384856	5238729
4	5338430	6495208	7429510	7429510	5387462
5	5238729	6986853	7449381	7449381	4663230
6	5334292	6194099	7241496	7241496	6194099
7	6205016	6762237	7244407	7244407	5334292
8	5387462	5338430	7296576	7296576	6616794
9	5986206	5238729	7344691	7344691	5986206
10	5938934	5387462	7479516	7479516	6205016

other hand, Japan can be regarded as technology leader of Great Britain, Israel, Korea, Mexico, Italy, France, Finland, and Taiwan. The US easily becomes the leading country of patented technologies due to its advantage of Sci-Tech resources and, of course, the large number of patents in very many aspects. But surprisingly, it is positive to see the clear boundary between the two domains led by different countries. This indicates positive technological diversification required for diverse ways of contribution to this society.

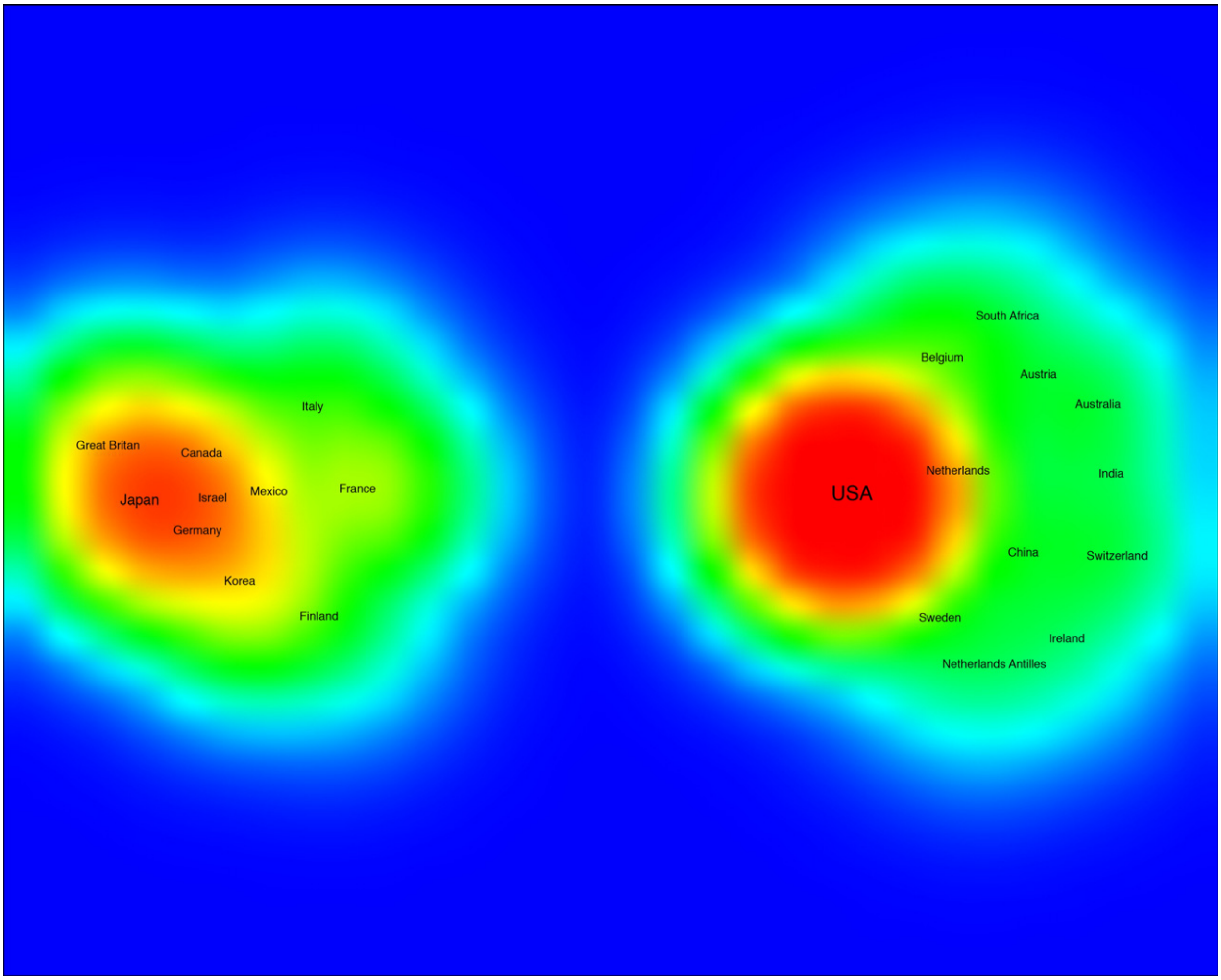

Fig. 7. 2-dimensional patent citation map with country as actor.

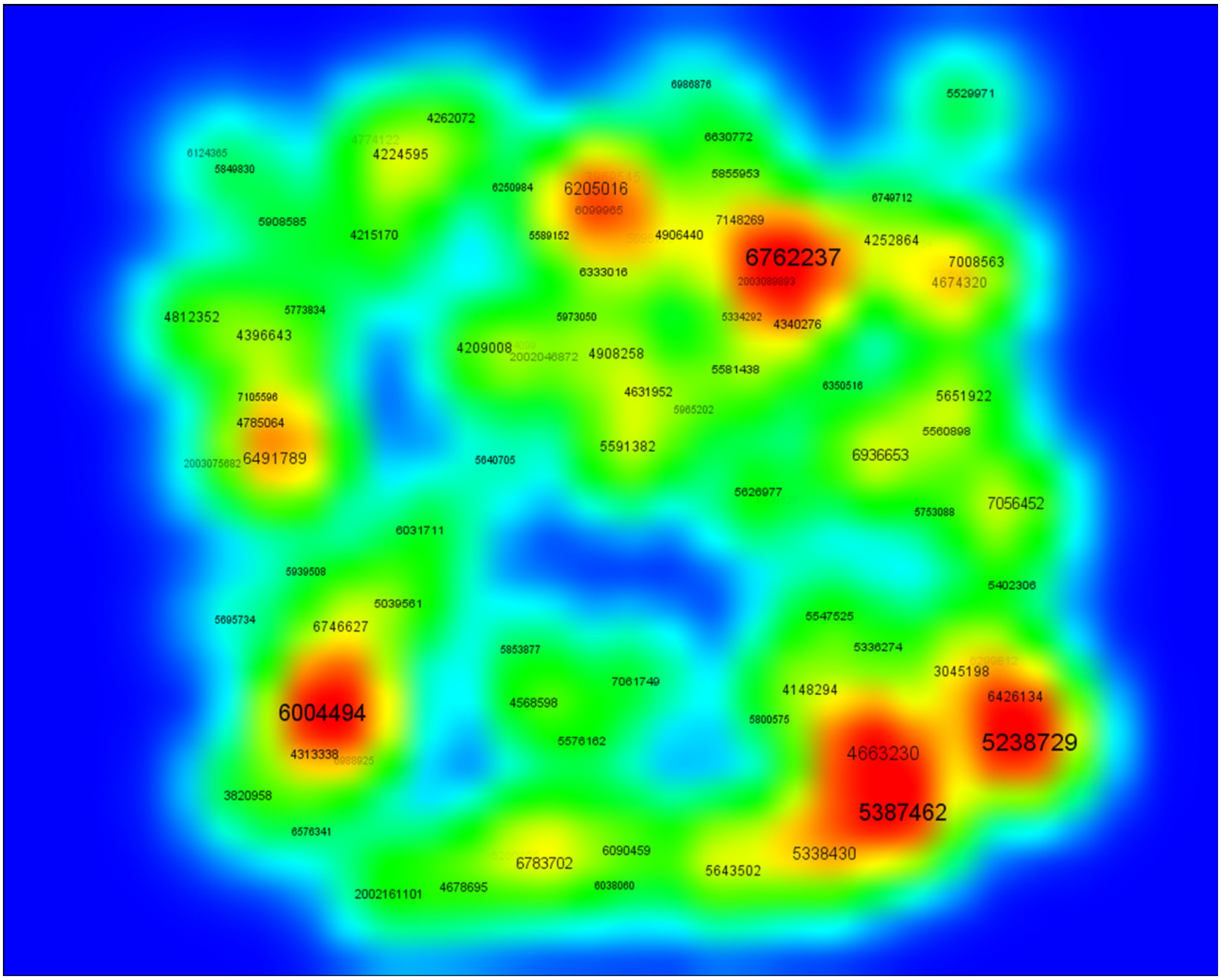

Fig. 8. 2-dimensional patent citation map with country as patent as actor.

The patent citation map with patent (shown as patent number) as actor in the map is shown in Fig. 8. A total of 113 patents with InDegree equal to or larger than 2 are selected to construct the map where relative distance between any pair of actors and density of InDegree for each actor can be visualized. Fig. 8 shows patents uniformly occupy different spots of the map and form a big continent, unlike isolated islands in Fig. 7, indicating well-distributed or highly concentrated patented techniques in this technology field.

4. Conclusion

Social network analysis on patent citation is demonstrated in this study to explore how patented technology development can be evolved from a patent citation network which visually represents the essential structure of technology evolution. Also, the linkages between the five different mechanisms of technology evolution and the five network properties, namely the concordance between technology evolution mechanisms and network properties, are defined and proposed in this study in order to provide a quantitative approach toward understanding technology evolution mechanisms for electrical conducting polymer nanocomposite technology. A patented technique plays multiple roles and shows different levels of importance in terms of the proposed five types of mechanism. The evolution mechanism represented by network property is a function of time in the overall technology development. Therefore, by calculating patents' network properties at different time points, a dynamic and quantitative understanding of technology evolution can be obtained.

According to the large number of patents in top 3 SICs in Table 2, it can be speculated that electrical conducting polymer nanocomposites are significantly applied on electric instrument, and the emerging nanotechnology combined with conventional nanocomposite material brings great influences on electronic components or scientific instrument.

The similar peak positions for Between Centrality curve and InDegree Centrality curve in Fig. 5 suggest technology diffusion and technology transition are closely associated together. Table 3 shows top centrality patents in one type of network property are easily to be top centrality again in other type of network properties. This suggests each mechanism of technology evolution does not happen alone but is supposed to be more or less associated to other type of mechanisms. In other words, critical patents are likely to be important in several aspects of technology evolution mechanisms.

It is found that 1984 and 1992, 1997–2001 are the important years for the development of electrical conducting polymer nanocomposite. US, Europe, Canada, Japan, Korea and Taiwan are major countries in this field. According to Standard Industry Classification, the largest portion of these patents is electronic components and scientific instruments. Endicott Interconnect Technologies, Zyvex Performance Materials, Minnesota Mining and Manufacturing Co., and Hyperion Catalysis International are core companies in electrical conducting polymer nanocomposite industry.

The length of a network tie in Figs. 2–4 is calculated for better visualization and has nothing to do with any network property. However, the length of a network tie can be proportional to similarity between two patents at both ends of a network tie, so it would be desirable to calculate similarity of two linked patents. For example, by calculating occurrence of same keyword in the two patents, and the obtained similarity can be used as the attribute of network tie. Text mining technique can possibly be applied on patents in each separated sub-domains in Figs. 2–4 to understand the differences among sub-domains, so deeper insight about how technology is evolved in each sub-domain can be employed in future study.

The 2-dimensional patent citation maps with country or patent as actor are shown in Figs. 7 and 8. This allows a straightforward view of the whole development of selected technology, and provides a quick idea of how the global technology has been developed, or a so-called knowledge map for positioning every patented technique in the patent citation map. However, this study only demonstrates the construction of patent citation map by the use of overall patents without considering time horizon. A dynamic map is also possible if we plot the 2-dimensional patent citation map for every year so the development over time can be observed.

In Summary, this study provides a way of patent evaluation and understanding technology development context in a systematic manner which facilitates more efficient technology management. Systematic methodologies involving citation analysis have been investigated in the field of technology forecast [57–59], but this study focuses more on systematic patent analysis and 2-dimensional visualization on the basis of conventional methods, and then demonstrates a systematic and quantitative way for analyzing and evaluating patented techniques by integrating basic patent statistics, technology–function classification, standard industrial classification, patent citation, network properties calculation and two-dimensional mapping. All of these contribute to a systematic approach for obtaining an overview of large amount of selected patents, more importantly this paper provides a quantitative way of evaluating patent and thus a computerized calculation is possible for potential quantitative applications e.g. R&D resource allocation, research performance evaluation, patent valuation, 2-dimensinol patent map visualization etc.

References

[1] T.S. Kuhn, J. Dewey, O. Neurath, The Structure of Scientific Revolutions, University of Chicago Press, Chicago, 1970.
[2] G. Dosi, Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change, Res. Policy 11 (1982) 147–162.
[3] R.N. Kostoff, H.J. Eberhart, D.R. Toothman, Database tomography for technical intelligence: a roadmap of the near-earth space science and technology literature, Inf. Process. Manag. 34 (1998) 69–85.
[4] R.N. Kostoff, R. Tshiteya, K.M. Pfeil, J.A. Humenik, Electrochemical power text mining using bibliometrics and database tomography, J. Power Sources 110 (2002) 163–176.
[5] R.N. Kostoff, R. Tshiteya, K.M. Pfeil, J.A. Humenik, G. Karypis, Power source roadmaps using bibliometrics and database tomography, Energy 30 (2005) 709–730.
[6] R.N. Kostoff, J. Antonio del R'ıo, H.D. Cortés, C. Smith, A. Smith, C. Wagner, L. Leydesdorff, G. Karypis, G. Malpohl, R. Tshiteya, The structure and infrastructure of Mexico's science and technology, Technol. Forecast. Soc. Change 72 (2005) 798–814.
[7] R.N. Kostoff, Literature-related discovery (LRD): introduction and background, Technol. Forecast. Soc. Change 75 (2) (2008) 165–185.
[8] R.N. Kostoff, Literature-related discovery (LRD): potential treatments for cataracts, Technol. Forecast. Soc. Change 75 (2) (2008) 215–225.
[9] R.N. Kostoff, S. Bhattacharya, M. Pecht, Assessment of China's and India's science and technology literature—introduction, background, and approach, Technol. Forecast. Soc. Change 74 (9) (2007) 1519–1538.
[10] R.N. Kostoff, D. Johnson, C.A. Bowles, S. Bhattacharya, A.S. Icenhour, K. Nikodym, R.B. Barth, S. Dodbele, Assessment of India's Research Literature, Technol. Forecast. Soc. Change 74 (2007) 1574–1608.
[11] R.N. Kostoff, M.B. Briggs, R.L. Rushenberg, C.A. Bowles, A.S. Icenhour, K.F. Nikodym, R.B. Barth, M. Pecht, Chinese science and technology—structure and infrastructure, Technol. Forecast. Soc. Change 74 (2007) 1539–1573.
[12] R.N. Kostoff, M.B. Briggs, R.L. Rushenberg, C.A. Bowles, M. Pecht, D. Johnson, S. Bhattacharya, A.S. Icenhour, K. Nikodym, R.B. Barth, Comparisons of the structure and infrastructure of Chinese and Indian Science and Technology, Technol. Forecast. Soc. Change 74 (2007) 1609–1630.
[13] R.N. Kostoff, R.G. Koytcheff, C.G. Lau, Global nanotechnology research literature overview, Technol. Forecast. Soc. Change 74 (2007) 1733–1747.
[14] R.N. Kostoff, J.A. Block, J.L. Solka, M.B. Briggs, R.L. Rushenberg, J.A. Stump, D. Johnson, T.J. Lyons, J.R. Wyatt, Literature-related discovery (LRD): lessons learned, and future research directions, Technol. Forecast. Soc. Change 75 (2) (2008) 276–299.
[15] R.N. Kostoff, M.B. Briggs, J.L. Solka, R.L. Rushenberg, Literature-related discovery (LRD): methodology, Technol. Forecast. Soc. Change 75 (2) (2008) 186–202.
[16] R.N. Kostoff, M.B. Briggs, T.J. Lyons, Literature-related discovery (LRD): potential treatments for Multiple Sclerosis, Technol. Forecast. Soc. Change 75 (2) (2008) 239–255.
[17] R.N. Kostoff, J.L. Solka, R.L. Rushenberg, J.A. Wyatt, Literature-related discovery (LRD): water purification, Technol. Forecast. Soc. Change 75 (2) (2008) 256–275.
[18] R.N. Kostoff, M.B. Briggs, Literature-related discovery (LRD): potential treatments for Parkinson's disease, Technol. Forecast. Soc. Change 5 (2) (2008) 226–238.
[19] R.N. Kostoff, Comparison of China/USA science and technology performance, Journal of Informetrics 2 (2008) 354–363.
[20] J. King, A review of bibliometric and other science indicators and their role in research evaluation, J. Inf. Sci. 13 (1987) 261.
[21] J. Law, J. Whittaker, Mapping acidification research: a test of the co-word method, Scientometrics 23 (1992) 417–461.
[22] B.M. Gupta, S. Bhattacharya, A bibliometric approach towards mapping the dynamics of science and technology, DESIDOC Bul. Inf. Technol. 24 (2004) 3–8.
[23] Y. Ding, G.G. Chowdhury, S. Foo, Bibliometric cartography of information retrieval research by using co-word analysis, Inf. Process. Manag. 37 (2001) 817–842.
[24] C. Baldwin, J. Hughes, T. Hope, R. Jacoby, S. Ziebland, Ethics and dementia: mapping the literature by bibliometric analysis, Int. J. Geriatr. Psychiatry 18 (1) (2003) 41–54.

[25] Y. Tian, C. Wen, S. Hong, Global scientific production on GIS research by bibliometric analysis from 1997 to 2006, Journal of Informetrics 2 (2008) 65–74.
[26] N. Coulter, I. Monarch, S. Konda, Software engineering as seen through its research literature: a study in co-word analysis, J. Am. Soc. Inf. Sci. 49 (1998).
[27] M. Callon, J.P. Courtial, F. Laville, Co-word analysis as a tool for describing the network of interactions between basic and technological research: the case of polymer chemistry, Scientometrics 22 (1991) 155–205.
[28] J.P. Courtial, A coword analysis of scientometrics, Scientometrics 31 (1994) 251–260.
[29] E.C.M. Noyons, A.F.J. Van Raan, Monitoring scientific developments from a dynamic perspective: self-organized structuring to map neural network research, J. Am. Soc. Inf. Sci. 49 (1) (1998) 68–81.
[30] A.F.J. Van Raan, R.J.W. Tijssen, The neural net of neural network research: an exercise in bibliometric mapping, Scientometrics 26 (1993) 169–192.
[31] A. Cambrosio, C. Limoges, J.P. Courtial, F. Laville, Historical scientometrics? Mapping over 70 years of biological safety research with coword analysis, Scientometrics 27 (1993) 119–143.
[32] E.C.M. Noyons, A.F.J. van Raan, Bibliometric cartography of scientific and technological developments of an R & D field, Scientometrics 30 (1994) 157–173.
[33] S. Hinze, Bibliographical cartography of an emerging interdisciplinary discipline: the case of bioelectronics, Scientometrics 29 (1994) 353–376.
[34] F. Rikken, H.A.L. Kiers, R. Vos, Mapping the dynamics of adverse drug reactions in subsequent time periods using INDSCAL, Scientometrics 3 (1995) 367–380.
[35] A. Clarke, M. Gatineau, M. Thorogood, N. Wyn-Roberts, Health promotion research literature in Europe 1995–2005, Eur. J. Public Health 17 (2007) 24.
[36] A. Rip, J.P. Courtial, Co-word maps of biotechnology: an example of cognitive scientometrics, Scientometrics 6 (1984) 381–400.
[37] M.A. De Looze, J. Lemarié, Corpus relevance through co-word analysis: an application to plant proteins, Scientometrics 39 (1997) 267–280.
[38] Y.S. Ho, Bibliometric analysis of adsorption technology in environmental science, J. Environ. Prot. Sci. 1 (2007) 1–11.
[39] S. Bhattacharya, P.K. Basu, Mapping a research area at the micro level using co-word analysis, Scientometrics 43 (1998) 359–372.
[40] W.T. Chiu, J.S. Huang, Y.S. Ho, Bibliometric analysis of severe acute respiratory syndrome-related research in the beginning stage, Scientometrics 61 (2004) 69–77.
[41] W.T. Chiu, Y.S. Ho, Bibliometric analysis of tsunami research, Scientometrics 73 (2007) 3–17.
[42] T. Li, Y.S. Ho, C.Y. Li, Bibliometric analysis on global Parkinson's disease research trends during 1991–2006, Neurosci. Lett. 441 (2008) 248–252.
[43] Y. Kajikawa, J. Yoshikawa, Y. Takeda, K. Matsushima, Tracking emerging technologies in energy research: toward a roadmap for sustainable energy, Technol. Forecast. Soc. Change 75 (2008) 771–782.
[44] Y. Kajikawa, Y. Takeda, Structure of research on biomass and bio-fuels: a citation-based approach, Technol. Forecast. Soc. Change 75 (2008) 1349–1359.
[45] Y. Kajikawa, Y. Takeda, Citation Network Analysis of Organic LEDs, Technol. Forecast. Soc. Change 76 (2009) 1115–1123.
[46] A.B. Jaffe, M. Trajtenberg, R. Henderson, Geographic localization of knowledge spillovers as evidenced by patent citations, Q. J. Econ. (1993) 577–598.
[47] S.B. Chang, K.K. Lai, S.M. Chang, Exploring technology diffusion and classification of business methods: using the patent citation network, Technol. Forecast. Soc. Change 76 (2009) 107–117.
[48] M. Acosta, D. Coronado, Science–technology flows in Spanish regions—an analysis of scientific citations in patents, Res. Policy 32 (2003) 1783–1803.
[49] B.H. Hall, A. Jaffe, M. Trajtenberg, Market value and patent citations, Rand J. Econ. (2005) 16–38.
[50] T.E. Stuart, J.M. Podolny, Local search and the evolution of technological capabilities, Strateg. Manage. J. 17 (1996) 21–38.
[51] E. Otte, R. Rousseau, Social network analysis: a powerful strategy, also for the information sciences, J. Inf. Sci. 28 (2002) 441.
[52] J. Liebowitz, Linking social network analysis with the analytic hierarchy process for knowledge mapping in organizations, J. Knowl. Manag. 9 (2005) 76–86.
[53] L.C. Freeman, Centrality in social networks: conceptual clarification, Social networks 1 (1979) 215–239.
[54] D.J. Brass, M.E. Burkhardt, Centrality and power in organizations, Networks and organizations: Structure, form and action 191 (1992) 215.
[55] M.S. Granovetter, The strength of weak ties, Am. J. Sociol. 78 (1973) 1360.
[56] Concordance Between the U.S. Patent Classification (USPC) System and the Standard Industrial Code (SIC) System, Patent Technology Monitoring Division (PTMD) Research Publications, Jun. 2008.
[57] D. Zhu, A.L. Porter, Automated extraction and visualization of information for technological intelligence and forecasting, Technol. Forecast. Soc. Change 69 (2002) 495–506.
[58] A.L. Porter, QTIP: quick technology intelligence processes, Technol. Forecast. Soc. Change 72 (2005) 1070–1081.
[59] T.U. Daim, G. Rueda, H. Martin, P. Gerdsri, Forecasting emerging technologies: use of bibliometrics and patent analysis, Technol. Forecast. Soc. Change 73 (2006) 981–1012.

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