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Networks of scientific journals: An exploration of Chinese patent data

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We apply social network analysis to display the characteristics of the networks resulting from bibliographic coupling of journals by the Chinese patent data of United States Patent and Trademark Office (USPTO) between 1995 and 2002. The networks of journals in all fields, the three strongly science-based fields (i.e. Biotechnology, Pharmaceuticals, and Organic Fine Chemistry), and the three weakly science-based fields (i.e. Optics, Telecommunications, and Consumer Electronics), have been analyzed from the global and the ego views, respectively. We study a variety of statistical properties of our networks, including number of actors, number of edges, size of the giant component, density, mean degree, clustering coefficient and the centralization measures of the network. We also highlight some apparent differences in the network structure between the subjects studied. Besides, we use the three centrality measures, i.e. degree, closeness, and betweenness, to identify the important journals in the network of all fields and those strongly science-based networks.

Introduction

Current society has become increasingly technology-driven and knowledge-based. Science and technology are often viewed as closely related, at times interacting systems. The role of science and relationship to technology has been a matter of great interest in policy makers and research communities. A substantial body of research has investigated the link between science and technology in a quantitative and especially bibliometric manner.

In these studies, patents and publications has been widely used as proxy output indicators of technological and scientific activity, respectively. Based on the various facets of linkages shown by these indicators, interactions between science and technology have been interpreted. Tracing publication activity of firms can throw some light on the industrial science connection [BHATTACHARYA & MEYER, 2003]. Identifying all patents that are owned by universities as well as patented technology invented by at least one university researcher can illuminate the technological aspects of scientific activity. Besides, tracing science/technology links includes the study of scientific articles authored in industry [GODIN, 1993, 1995], co-authored publications

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by industry and academe [CHONG & AL., 2003] and patents cited in the scientific literature [GLÄNZEL & MEYER, 2003]. However, the majority of the quantitative contributions focus on analyzing the scientific literature cited in patents, so-called non-patent references (NPRs). This approach of patent citation analysis was pioneered by CARPENTER & NARIN [1983], and NARIN & NOMA [1985], and has become the most popular method to determine the interplay between science and technology [VERBEEK & AL., 2002; MEYER, 2006; GUAN & HE, 2007]. MEYER [2000] pointed out that citation links between patents and papers signify, if not explicitly, at least implicitly the contribution of science to technology. The non-patent references in patent documents were deemed as indicator of "science-intensity or science proximity of patents" [VAN LOOY & AL., 2003; CALLAERT & AL., 2006; VAN LOOY & AL., 2006].

The relationship between science and technology as a complex interplay between them is now more acceptable. The different forms of direct and indirect contributions science makes to technology, and vice versa, pose challenges to the measurement of science–technology exchange [MEYER, 2006]. Social network analysis (SNA) proved to be a promising method for understanding the complex relations between various actors, such as industry and academe, inventors within organizations, organizations with regions, and so forth. This approach was developed mainly by sociologists and researchers in social psychologists, and further developed in collaboration with mathematics, statistics and physicists. It can be used for identifying the structures in social systems based on the relations among the system's components rather than the attributes of individual cases [LATOUR, 1987; OTTE & ROUSSEAU, 2002; WASSERMAN & FAUST, 1994]. Extensive empirical and theoretical studies on social network analysis have been carried out. Some recent examples include the work of NEWMAN [2001A, 2001B, 2001C], who studied a variety of statistical properties, nonlocal statistics and the structure of scientific collaboration networks. GIRVAN & NEWMAN [2002] explored the property of community structure in social and biological networks. BALCONI & AL. [2004] focused on the specific role of academic inventors in different technological classes based on the Italian networks of inventors. METCALFE [2006] discovered the indirect connections between industry and the academy as seen through sponsorship relations between corporations and associations. CANTNER & GRAF [2006] described the evolution of the innovator network of Jena, Germany during the period from 1995 to 2001. INOUE & AL. [2007] analyzed the network of Japanese patents, especially focusing on its spatial characteristics.

There is an evident difference as compared bibliometric analysis or patent citation analysis with Social network analysis (SNA). Social network analysis is not a formal theory in sociology but rather a strategy for investigating social structures [OTTE & ROUSSEAU, 2002]. The traditionally individualistic approach, such as bibliometric analysis or patent citation analysis, considers only properties of individual actors without taking the behavior of others into consideration. In SNA, however, the relationships between actors become the first priority, and individual properties are only secondary [OTTE & ROUSSEAU, 2002]. KNOKE & KUKLINSKI [1982] pointed out that individual characteristics as well as relational links are necessary in order to fully understand social phenomena.

In the case of GUAN & HE [2007], they applied patent citation analysis to explore the characteristics and pattern of the linkage between science and technology in China, based on Chinese patent data of United States Patent and Trademark Office (USPTO) during 1995–2004. In this paper, we combine patent citation analysis with SNA to further investigate the interaction between science and technology in China. The analysis is mainly focused on networks resulting from bibliographic coupling of journals by the Chinese patent data of United States Patent and Trademark Office (USPTO) between 1995 and 2002. The bibliographic coupling technique is often used to construct the connections between the studied objects. (e.g., [EGGHE & ROUSSEAU, 2002; HUANG & AL 2003; AHLGREN & JARNEVING, 2008]) There have been some studies on journal networks. MARTINSONS & AL. [2001] studied the network of journals in the field of strategic management and showed this field has entered the mainstream of social science. LEYDESDORFF & ZHOU [2007] constructed the network of journals, which is based on the *Journal Citation Reports of the Science Citation Index*, and delineated a core set of nanotechnology journals and a nanotechnology-relevant set. LEYDESDORFF [2007A] proposed that the betweenness centrality is an indicator of the interdisciplinarity of journals, and then used it to a variety of citation environment. There is a common property in these studies: journal networks are generated on journal-to-journal citation environment. However, in this paper we expect to construct the network of journals using the data of patents, and further explore the properties of the network of journals from the global and ego views, respectively.

Data and journal networks

Patents provide information on patent citations, namely citations to scientific references as well as patents. NPRs comprise a variety of documents, such as journal articles, conference papers, technical papers, text books, technical bulletins, abstracting services, and so on. We call journal articles and conference papers as scientific NPRs. Those scientific NPRs are appropriate proxy to indicate and quantify the relation between technological inventions to scientific research [GRUPP, 1996; GRUPP & AL., 1996; LEYDESDORFF, 2004; GUAN & HE, 2007]. On the other hand, in order to investigate the structure of journal networks resulting from patent data, special attention will be paid to journal articles, especially journal publications covered by Science Citation Index (SCI).

We use data on patents that were applied for at USPTO and disclosed between 1995 and 2002. To include all patents that are relevant to China, we filtered out all patents where there is at least one of Chinese inventors on the patent at the time of application. Here we only focus on utility patents because they represent the progress of technology and more closely connect to scientific research. Altogether we could identify 2546 utility patents, covering 5361 scientific NPRs. 3560 out of 5361 scientific NPRs are SCI journal papers, distributing on 724 SCI journals. Thus, we set up a patent-journal database, which is composed of patent numbers and their corresponding SCI journals.

The patent-journal database permits us to construct a network of SCI journals, based upon Chinese patent data from USPTO. The following hypothetical example illustrates the main idea (see Figure 1).

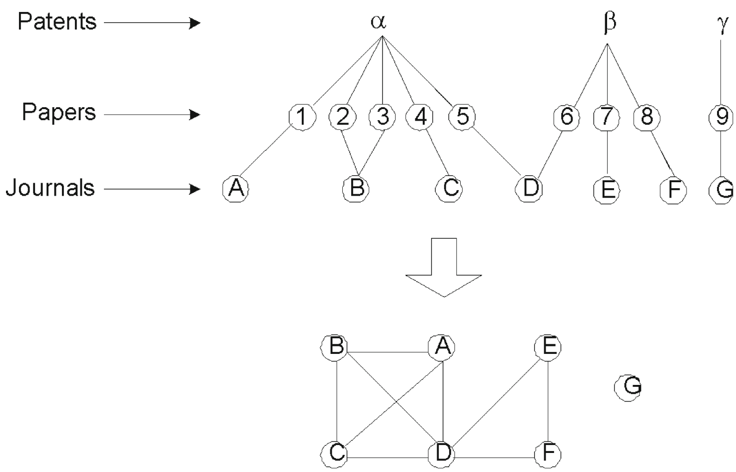

Figure 1. Bipartite graph representation of the network of scientific journals

Let us suppose we face nine papers [1–9], coming from three different patents (α,β,γ). Nine papers have been produced by seven journals (A–G). So, for example, patent α has five scientific references of journal papers [1–5], deriving from four different journals (A–D). Besides, journal B is responsible for two papers [2, 3]. More precisely, patent α is produced on a scientific base comprising journals A–D. A reasonable assumption to make at this point is that non-patent citations within a patent can be taken as "representative for the scientific base of the citing patents" [PAVITT & SOETE, 1980].

Due to the providers of the scientific source for a common citing patent, the four journals are 'linked' to each other by such knowledge relation. The existence of such linkage can be graphically represented by drawing an undirected arrow between each pair of journals, as shown on the bottom part of Figure 1. The size of the node corresponds to the citation times that each journal obtains within the citation environment of patents. The width of the lines corresponds to the strength of the relation between each pair of nodes, namely, linked times between each pair of journals. Repeating the same exercise for each group of journals, we end up with a map representing the network of linkage among all journals. In other words, we obtain the undirected networks of scientific journals pertaining to Chinese patent data during the period of 1995–2002. Our networks are generated by the bibliographic coupling of journals by patents. We call them journal networks in the remainder of the article.

Empirical results

Social network analyses include two main forms: the ego network analysis, and the global network analysis. In ego network analyses the network of one person is analyzed. In global analyses one tries to find all relations between the participants in the network [OTTE & ROUSSEAU, 2002]. In this section we mainly view the networks from 'global' and 'ego' perspectives, respectively.

Global view of the networks

In the following, we first identify eleven scientific oriented technological fields, and then focus our attention to the three strongly science-based fields and another three weakly science-based fields. Next, pertaining to the network of all fields and the networks of the above six technologies we study a variety of statistic properties of the networks, including number of actors, number of edges, size of the giant component, density, mean degree, clustering coefficient and the centralization of the network.

Bibliometric description of science intensive technologies

It is now more accepted that some technologies are strongly related to scientific development and others where this relatedness is more tenuous [VERBEEK & AL., 2002]. The science connection strongly differentiates between technological sectors and yet tenuously between countries [GRUPP, 1996]. Using the scientific non-patent references (NPRs) within the Chinese patents from USPTO between 1995 and 2002, GUAN & HE [2007] investigate the science-technology linkage in eleven scientific oriented technological fields specified by OECD [2004] and the Fraunhofer Gesellschaft-Institute für Systemtechnik und Innovationsforschung (FhG-ISI, Germany). Based on their empirical research, we can obtain two findings. First of all, for China the difference of science intensity between technologies becomes obvious. Second, there is a gap between a ‘cluster’ of strongly science-based technologies (i.e. biotechnology, pharmaceuticals, and organic fine chemistry) and a ‘cluster’ of weakly science-based technologies (i.e. optics, telecommunications, and consumer electronics). Hence, we pay special attention to the above six technological domains.

Table 1 summarizes the science intensity and SCI-journal counts pertaining to all technology fields in total and the above six fields, namely Biotechnology, Pharmaceuticals, Organic Fine Chemistry, Optics, Telecommunications, and Consumer Electronics in the studied period. In terms of the science intensity, i.e. number of scientific references cited per patent, the average Science Intensity in all technology fields is 2.1. The science intensity for the six technologies varies from a high of 12.29 to a low of 0.46. Biotechnology, Pharmaceutical and Organic fine chemistry distinguish them with very high degree of Science Intensity, which are all far higher than the average level. We call these three fields as the strongly science-based fields. On the contrary, as for the fields of Optics, Telecommunication and Consumer Electronics, the values of Science Intensity are all lower than the average level, less than 1.0. Similarly, these three fields are named as the weakly science-based fields. Besides, among the selected fields, Pharmaceutical takes the first position with 2092 scientific references to patents, including 844 papers distributed on the 319 journals covered by SCI. On the other hand, the least scientific literatures are observed in Consumer Electronics, only including 42 scientific references to patents. 15 out of them are published on the 13 journals indexed by SCI. It is obvious that the scientific journals covered by SCI are skewed distributed in the selected technological areas.

Table 1. Science intensity and SCI-journal counts, by technology fields, 1995–2002

Technological fields	Patent counts	Scientific NPRs	Science Intensity	SCI NPRs	SCI-journal counts
All technology fields	2546	5361	2.1	3560	724
Biotechnology	85	1045	12.29	477	201
Pharmaceutical	206	2092	10.16	844	319
Organic fine chemistry	202	1674	8.29	653	263
Optics	115	71	0.62	27	25
Telecommunications	137	74	0.54	15	14
Consumer Electronics	92	42	0.46	15	13

Source: USPTO database (http://www.uspto.gov)
Remarks: Scientific NPRs includes journal articles and conference papers. SCI NPRs denote papers covered by Science Citation Index (SCI). Science intensity is the ratio between the number of patents and the total number of Scientific NPRs registered at USPTO between 1995 and 2002.

It is interesting to explore the characteristics of journal networks generated by all fields and the selected six technological areas.

General properties of journal networks

The general properties of the Chinese network of SCI journals are summed up in Table 2, both for the overall network and for the six nested network, each of them built by considering only the utility patents belonging to specific technological fields such as Biotechnology, Pharmaceuticals, Organic Fine Chemistry, Optics, Telecommunications, and Consumer Electronics. Besides, in the following sub-sections we only consider networks without loops and multiple lines.

Table 2. Networks of scientific journals from Chinese patent data, by technology fields,1995–2002

	All fields	Biotechnology	Pharmaceuticals	Organic Fine Chemistry	Optics	Telecom-munications	Consumer Electronics
Number of journals	724	201	319	263	25	14	13
Number of links connecting journals	7634	1844	4126	3007	61	11	9
Number of journals with no links to any other journals	47	2	7	4	3	3	5
Number of components	55	4	11	8	7	7	7
Density	0.0297	0.0917	0.0813	0.0873	0.2033	0.1209	0.1154
Largest component							
Diameter	7	4	5	6	1	1	2
Number (and % of total) of journals in the component	662 (91.43)	197 (98.01)	304 (95.30)	253 (96.20)	10 (40.00)	4 (28.57)	5 (38.46)
Mean degree	21.09	18.34	25.86	22.87	4.88	1.5714	1.3846
clustering coefficient	0.0425	0.0809	0.0916	0.0941	0.52	0.4286	0.2949
Average distance among reachable pairs	2.673	2.147	2.2446	2.2842	1.0896	1	1.3077

We first notice that the number of actors and edges across networks differ widely. The network in all fields has considerably 724 actors and 7634 edges. The networks for those strongly science-based fields i.e. Biotechnology, Pharmaceuticals, Organic Fine Chemistry, own no less 200 actors and 1800 edges while those of weakly science-based fields i.e. Optics, Telecommunications, and Consumer Electronics, have extremely low number of actors and edges. Thus the networks can be divided into three groups, namely the network of all fields, strongly science-based networks (Biotechnology, Pharmaceuticals, and Organic Fine Chemistry) and weakly science-based networks (Optics, Telecommunications, and Consumer Electronics).

The size of components for those networks varies from 55 to 4. Measuring the size of groups of connected journals in each network, we find that in the network of all fields and strongly science-based networks, the largest component fills more than 90% of all journals, especially the giant component of Biotechnology network containing about 98% of all journals. It appears that the largest components we mentioned above are as big as or bigger than the giant components of scientific collaboration networks identified by NEWMAN [2001A]. The figure of more than 90% for the size of the largest component is a promising one. It indicates that vast majority of journals are connected via knowledge relations. On the other hand, in weakly science-based networks, the fraction is smaller and no less than 40% of total size of the network. This occurred because that there are less vertices and edges, and more isolated vertices in those weakly science-based networks. NEWMAN [2001A; 2001C] has pointed out that with increasing density of edges in a graph, a 'giant component' forms, i.e., a connected subset of vertices whose size scales extensively. The diameter of the largest component (i.e. the length of the largest geodesic between any pair of nodes) gives rough indication of how effective in the network is in linking pairs of journals in the component. Such diameters measure less than 7 in all of networks. Particularly in the network of all fields and those strongly science-based networks, the diameters of the giant components are still small, despite the large size of the components. Another more precise indicator of the efficiency in communication path is the average distance among all reachable pairs of journals in a network. The average distance between all reachable pairs of journals for each of the networks studied here is all less than 3. Even in the relatively large network such as the network of all fields and strongly science-based networks, it takes an average of only about three or two steps to reach a randomly chosen journal from any other of the network. The existence of a large giant component, as discussed above, allow 'information' to reach most members of the network faster.

The density of the journal networks also varies across technologies. The density of those weakly science-based networks is higher than that of other networks. The possible reason is that the density of a network depends on the size of the network. Average degree of all actors is another indicator of measuring the structure cohesion of a network, which is independent of the size of a network. As shown in Table 2, the average degree of the network is the highest in Pharmaceutical, followed by Organic Fine Chemistry. This implies that the possibility for two journals in the Pharmaceutical field to get in touch through a chain of patents is much higher than in other fields, despite the much larger size of the network they are embedded in. Another structure measure for a network is the overall clustering coefficient. In Table 2, we can see that three is a very strong clustering effect in Optics: two journals have a 50% or greater possibility of being connected if both have connected with the third journal. The network of all fields and the three strong science-based networks all possess much lower values of the clustering coefficient than the weakly science-based networks.

Centralization of journal networks

The concepts of centrality and centralization are two of the oldest concepts in social network analysis. Here we focus on the network centralization, which mainly includes degree centralization, closeness centralization and betweenness centralization. The centralization of a network is higher if it contains very central vertices as well as very peripheral vertices. It can be computed from the centrality scores of the vertices within the network: more variation in centrality scores means a more centralized network [DE NOOY & AL., 2005].

The centralization of journal networks is presented in Table 3. In terms of the degree centralization and betweenness centralization, the Biotechnology network has the highest values of centralization among all networks. It should be pointed out that closeness centrality cannot be calculated on a network, which is not fully connected. Here the closeness centralization is computed on the giant component of each network. The value of closeness centralization for the Biotechnology network is also highest except for the Consumer Electronics. Overall, it suggests that the Biotechnology network is the most centralized in all networks. This means in the Biotechnology network there is a clear boundary between the center and the periphery. On the contrary, the Telecommunication is the least centralized in that it has lowest values of centralization among all networks. More precisely, the values of betweenness centralization and closeness centralization are zero. This occurred because that the variation of the centrality scores of the vertices is zero.

Table 3. Three indicators of centralization in scientific journal networks

Centralization	All fields	Biotechnology	Pharmaceuticals	Organic Fine Chemistry	Optics	Telecom munication	Consumer Electronics
Degree	0.3952	0.6699	0.5384	0.5659	0.1866	0.1282	0.2576
Betweeness	0.1467	0.3636	0.1453	0.1646	0.0217	0	0.0606
Closeness*	0.4508	0.6835	0.5622	0.532	0	0	0.7778

Remarks: *: Closeness centralization is calculated for the largest component (i.e. giant component).

Ego view of the networks

Most social networks contain people or organizations that are central. Ego network analysis recognizes the position of nodes by virtue of their relation to other nodes. The concept of centrality is based on the simple idea that information may easily reach actors who are central in the given network. In other words, if social relations are channels that transmit information between individual actors, central actors are those have better access to information or may control the spread of information. The most important centrality measures of vertices are: degree centrality, closeness centrality and betweenness centrality. On the other hand, from the above global analysis of the networks we find that networks for all fields, Biotechnology, Pharmaceuticals, Organic Fine Chemistry are highly connected and the size of the networks are relatively large, containing more actors and edges. On the contrary, the size of networks for Optics, Telecommunications, and Consumer Electronics is far small, including less actors (journals) and edges. In this sub-section, using these centrality measures, we expect to find the relative prominent and more important actors (journals) in different networks. Therefore, we pay more attentions to the networks of large size, namely the network of all fields and those strongly science-based networks. In addition, we expect those important journals to differ across technological fields. Findings for these centrality measures across technological fields are discussed below, with descriptive statistics shown from Table 4 to Table 9.

Centrality measures for the network of all fields

Before conducting the analysis, we take a close look at the difference between these centrality measures. Degree centrality and closeness centrality rests on the idea of the reachability of an actor within a network. More precisely, if you are closer to the other actors in the network, the paths that information has to follow to reach you are shorter, so it is easier for you to get information [DE NOOY & AL., 2005]. In a simple undirected network, if we consider direct neighbors of a vertex only, degree centrality is a simple measure of centrality. If we also take into account of indirect contact, we use closeness centrality, which is based on the total distance between one vertex and all other vertices. The importance of a vertex to the circulation of information is captured by the concept of betweenness centrality. This indicator qualifies who the most influential actors in the network are, the ones who control the flow of information between most others [NEWMAN, 2001B].

Table 4 provides the top 10 journals using the three centrality measures in the network of all technological fields. We first examine degree centrality and closeness centrality (see first fourth column in Table 4). As shown in Table 4, those journals with high degree centrality can be roughly expected to have also a high closeness centrality. As compared the first column with the third column, we find that the set for the degree almost overlaps with closeness, and the two sets differ only by a single journals: the *Cell* is included in the first set, and the *Journal of the Chemical Society* belongs to the latter. More precisely, nine of ten journals occur on both lists, and the order of the top four journals is the same. Degree centrality shows a highest value for the *Proceedings of the National Academy of Sciences of the United States of America (PNAS)*. *Nature* is surpassed on this indicator by *Science*, which has a value of 0.3831.

Table 4. Top 10 journals on three indicators of centrality in all technology fields

	Degree		Closeness		Betweenness
PNAS	0.4232	*PNAS*	0.6092	*Science*	0.1484
Science	0.3831	*Science*	0.5998	*PNAS*	0.1217
Nature	0.2960	*Nature*	0.5693	*Nature*	0.1186
J. Biol. Chem.	0.2324	*J. Biol. Chem.*	0.5192	*J. Am. Chem Soc.*	0.0364
Biochemistry	0.2102	*J. Am. Chem. Soc.*	0.5188	*Appl. Phys. Lett.*	0.0350
J. Med. Chem.	0.2089	*Cancer Res.*	0.5148	*Chem. Pharm. Bull.*	0.0308
BBRC	0.1978	*Biochemistry*	0.5139	*J. Org. Chem.*	0.0290
Cancer Res.	0.1950	*BBRC*	0.5088	*Cancer Res.*	0.0288
J. Am. Chem. Soc.	0.1936	*J. Med. Chem.*	0.5072	*J. Biol. Chem.*	0.0256
Cell	0.1715	*J. Chem. Soc.*	0.4988	*J. Med. Chem.*	0.0198

More precisely, *PNAS* has a highest of 306 links to other journals, followed by *Science* and *Nature* with 207 and 214 ties, respectively. These three journals can be understood to share the most prominent position in the network in terms of relationships to others. In terms of closeness centrality, the *PNAS* also occupy the first position with a score of

0.6029, followed by *Science* and *Nature*, respectively. The closeness centrality of a vertex is higher if the total distance to all other vertices is shorter. It suggests that it takes the 'minimum steps' for the *PNAS* to reach other journals in the network. In terms of betweenness, the main difference that is visible in Table 4 is the skewness of its distribution as compared with the other two measures. Only a few journals have a high betweenness centrality. The highest value for betweenness centrality among these journals is the *Science.* Other journals follow with slightly lower values, among them *PNAS* with 0.1217 and *Nature* with 0.1186. It implies that the *Science* is situated on the geodesics between many pairs of vertices, so it is crucial to transmit the information through the network. Besides, there are obvious differences from the top 10 list in betweenness as compared with the top 10 lists in degree and closeness. For example, *Applied Physics Letters,* which is frequently cited in ICT areas, occupies 5th on the list of betweenness, and it is not included in the two lists of the other centrality measures. It is clear that the *PNAS* and *Science* have the highest centrality at global level, no matter how one measures the indicator.

Table 5 provides the top 10 journals in terms of the paper citations in Chinese patents of USPTO during the period of 1995 to 2002. The most frequently cited journal is a Chemistry journal, i.e. *Journal of Medicinal Chemistry*, with 142 papers cited in Chinese patents of USPTO. Closely followed journal is the *PNAS,* where 136 papers are cited. *Science* and *Nature* are also frequently cited, taking the third and the fourth positions, respectively. Similar findings for the three multidisciplinary journals have been presented for the science-technology interactions in VERBEEK & AL. [2002] on USPTO patents during 1992–1996. Besides, the *Applied Physics Letters* also appears on this list.

As compared Table 4 with Table 5, we first find that the leading journal: *Journal of Medicinal Chemistry* in Table 5 is ranked in the middle or on the bottom of the columns in Table 4. Further analysis shows that multidisciplinary journals like the *PNAS*, *Science* and *Nature*, all occur on those three columns in Table 4, and take the top positions on these lists. Similar findings have also been presented in LEYDESDORFF [2007] on 7379 journals, harvested from Journal Citation Report of the Science Citation Index and the Social Sciences Citation Index 2004.

Besides, VERBEEK & AL. [2002] pointed out that the *PNAS*, *Science* and *Nature* also frequently appear in USPTO patents during 1992–1996. It therefore suggests that in most of the cases the *PNAS*, *Science* and *Nature,* the three famous multidisciplinary journals, are read mostly by patent inventors and examiners. In other words, patent inventors and examiners don't read specialized journals that much. In addition, each of columns in Table 4 and Table 5 includes relatively more Chemistry journals like *Journal of Medicinal Chemistry*, *Journal of Biological Chemistry*, *Journal of the American Chemical Society* and *Journal of Organic Chemistry*, and so on. It implies that those Chemistry journals are also the important science base of the Chinese patents.

Table 5. Top 10 journals ranked by paper citations of Chinese patents for all fields

Journals	Paper citations	Category
J. Med. Chem.	142	Chemistry, Medicinal
Proc. Natl. Acad. Sci. USA.	136	Multidisciplinary Sciences
Science	120	Multidisciplinary Sciences
Nature	90	Multidisciplinary Sciences
J. Biol. Chem.	60	Biochemistry & Molecular Biology
J. Am. Chem. Soc.	57	Chemistry, Multidisciplinary
Appl. Phys. Lett.	49	Physics, Applied
J. Org. Chem.	49	Chemistry, Organic
Cancer Res.	48	Oncology
Anal. Chem.	44	Chemistry, Analytical

Let us now turn back to the third row in Table 2. We find that 47 journals are isolates, which means that there is no link with any other journals for the 47 journals. The rest journals have more or less links with others. Next, we will take the link strength between each pair of journals into account. If a patent cites journal A and journal B, there is a link between A and B. Therefore, the link strength between journal A and journal B is the times journal A has connected with journal B. In other words, the number of patents citing journal A and B simultaneously, is the link strength between journal A and journal B. In addition, ties between journals are so dense that links can not be seen clearly. Therefore, we must omit large numbers of lines for clarity. Here, we care much about those strongly connected edges, so we remove lines with value less than 20 to obtain a clear sub-network, only including those strongly linked edges and corresponding vertices.

Figure 2 provides the visualization of these strongly linked journals with line value more than 20 for the network of all fields. The width of the lines corresponds to the strength of the relation between each pair of nodes, namely, linked times between each pair of journals. Visual inspection of Figure 2 suggests that these two journals (*PNAS* and *Science*) are central in relating to other journals. The linkage between *PNAS* and *Science* is the strongest among all links in the network, because the width of the line between them is the thickest. More precisely, the value of line between *PNAS* and *Science* is 70, which means that the *PNAS* and the *Science* are cited simultaneously by 70 patents. The link strength between *Nature* and *Science* is 50, with the second-thickest line. The link strength between *Nature* and *PNAS* is similar to that of *Biochemistry* and *PNAS*, tied for the third place. The above findings show that these three journals, i.e. *PNAS*, *Science*, and *Nature*, are co-cited most frequently by patents.

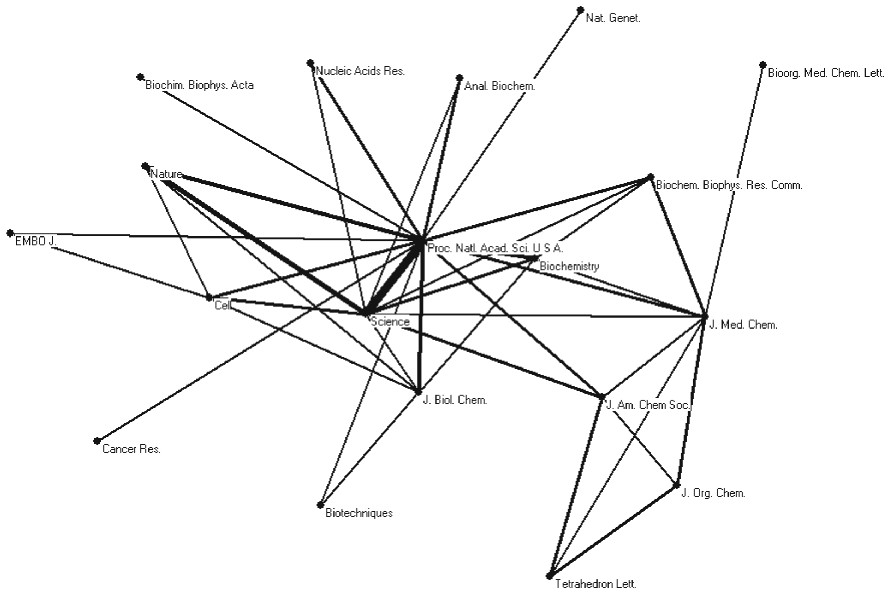

Figure 2. Strongly linked journals with line value more than 20 for the network of all fields

Centrality measures for the network of the three strongly science-based fields

As mentioned above, the three fields, i.e. Biotechnology, Pharmaceutical and Organic fine chemistry, are called as the strongly science-based fields. Next, we will focus on the centrality measures of the three networks, reported from Table 6 to Table 8, respectively.

For Biotechnology shown by Table 6, the set for the degree overlaps with closeness except for the order of two journals, i.e. the *Nucleic Acids Research* and *Nature* are different. Besieds, these two sets differ only by two journals from the list for betweenness: the *Biotechnology and Bioengineering* and the *Plant Physiology* are included in the latter set, instead, *FEBS Letter* and the *Molecular Genetics and Genomics* are included in former two sets. Table 6 also shows a strong skewness in the distribution of betweenness centrality as compared with the other two measures. Only the *PNAS* has a high betweenness centrality of 0.3673, and others are all less than 0.1. It therefore suggests that *PNAS* is more central in controlling the information due to its position in the network. In terms of these three centrality measures, the first and the second positions are all occupied by these two multidisciplinary journals, i.e. the *PNAS* and *Science*, respectively.

Table 6. Top 10 journals on three indicators of centrality in the field of Biotechnology

	Degree		Closeness		Betweeness
PNAS	0.755	*PNAS*	0.8133	*PNAS*	0.3673
Science	0.485	*Science*	0.6555	*Science*	0.0808
Nature	0.395	*Nucleic Acids Res.*	0.6164	*Nucleic Acids Res.*	0.0485
Nucleic Acids Res.	0.39	*Nature*	0.6164	*Gene*	0.0483
Gene	0.355	*Gene*	0.5994	*Nature*	0.0473
Cell	0.325	*Cell*	0.5921	*J. Biol. Chem.*	0.0395
Biotechniques	0.315	*Biotechniques*	0.5833	*Biotechnol. Bioeng.*	0.0386
J. Biol. Chem.	0.285	*J. Biol. Chem.*	0.5748	*Plant Physiol.*	0.0356
FEBS Lett.	0.26	*FEBS Lett.*	0.5681	*Cell*	0.0253
Mol. Genet. Gen.	0.24	*Mol. Genet. Gen.*	0.56	*Biotechniques*	0.0247

Table 7. Top 10 journals on three indicators of centrality in the field of Pharmaceutical

	Degree		Closeness		Betweeness
PNAS	0.6163	*PNAS*	0.7354	*PNAS*	0.1484
J. Med. Chem.	0.4591	*Science*	0.6406	*Chem. Pharm. Bull.*	0.0703
Science	0.4528	*J. Med. Chem.*	0.6352	*J. Med. Chem.*	0.0624
BBRC	0.4339	*BBRC*	0.6273	*Science*	0.0603
J. Biol. Chem.	0.4308	*J. Biol. Chem.*	0.6171	*Cancer Res.*	0.0530
Nature	0.3836	*Nature*	0.6060	*J. Biol. Chem.*	0.0521
Cancer Res.	0.3584	*Cancer Res.*	0.6012	*BBRC*	0.0513
Biochemistry	0.327	*Biochemistry*	0.5771	*Nature*	0.0479
Chem. Pharm. Bull.	0.3113	*Cell*	0.5739	*Toxicon*	0.0412
J. Am. Chem. Soc.	0.2987	*Chem. Pharm. Bull.*	0.5695	*J. Org. Chem.*	0.0332

For Pharmaceutical shown by Table 7, the set for degree centrality overlaps with closeness and these two sets differ only by a single journal: the *Journal of the American Chemical Society* is included in the former, and the *Cell* is instead incorporated into the latter. Besides, like the field of Biotechnology, the *PNAS* has the highest centrality at global level, no matter which of the indicators is concerned. In terms of degree centrality, the second is taken by the *Journal of Medicinal Chemistry*, followed by the *Science*. Closeness centrality also shows a second highest value for the *Science*, which is same as the closeness of the Biotechnology. The highest value of betweenness centrality is again for the *PNAS* (0.1484), and other journals follow with significantly lower values, among them the *Chemical and Pharmaceutical Bulletin* with 0.0703 places in the second position. However, in terms of the other two centrality measures, the *Chemical and Pharmaceutical Bulletin* is ranked on the bottom of the lists. The set for betweenness is differ widely from the above two sets. It suggests that the three measures may indicate different dimensions, but they do not discriminate among one another to provide us with a measure of importance of the actors at the level of the network.

Table 8. Top 10 journals on three indicators of centrality in the field of Organic Fine Chemistry

	Degree		Closeness		Betweeness
PNAS	0.6488	*PNAS*	0.7159	*PNAS*	0.1685
Science	0.5076	*Science*	0.6412	*Science*	0.0893
Nature	0.4504	*Nature*	0.6238	*Nature*	0.0814
J. Med. Chem.	0.4122	*J. Med. Chem.*	0.6176	*J. Med. Chem.*	0.0726
Biochemistry	0.3969	*Biochemistry*	0.5972	*Tetrahedron Lett.*	0.0690
Tetrahedron Lett.	0.3855	*Tetrahedron Lett.*	0.5943	*J. Org. Chem.*	0.0602
J. Biol. Chem.	0.3779	*Cancer Res.*	0.5902	*J. Biol. Chem.*	0.0512
Cancer Res.	0.3664	*J. Biol. Chem.*	0.5874	*BMCL*	0.0381
J. Biochem.	0.3321	*J. Org. Chem.*	0.5807	*Cancer Res.*	0.0379
J. Org. Chem.	0.3129	*J. Biochem.*	0.5688	*Polymer*	0.0361

For the Organic Fine Chemistry shown by Table 7, the set for degree centrality overlap completely with closeness. Eight of the 10 journals in betweenness set occur on both lists of other two measures, and the order of the top four, namely the *PNAS*, the *Science*, the *Nature* and *Journal of Medicinal Chemistry*, is the same. As before, the betweenness centrality is not distributed equally among journals. The *PNAS* has a betweenness centrality of 0.1685, leading the first position. The *Science* is second on this indicator with a value of 0.0893.

Table 9 shows the top 10 journals sorted by the number of papers cited in Chinese USPTO patents in the three science-based fields, respectively. For the Biotechnology (see first and second columns), the *PNAS* leads the first with 28 citations, followed by *Journal of Biological Chemistry* with 26 citations. *Science* has been cited 17, taking the third. For the Pharmaceutical (see third and forth columns), the journal cited most by Chinese patents is the *Journal of Biological Chemistry*, followed by the *PNAS* and the *Journal of Medicinal Chemistry,* respectively. For the Organic Fine Chemistry (see fifth and sixth columns), the *Journal of Biological Chemistry* is the highest among all journals, with a score of 26. The second and the third are occupied by the *PNAS* and the *Journal of Medicinal Chemistry*, respectively. Taking from Table 6 to Table 9 into account together, we find that patents of different fields have different knowledge base. Those journals of biochemistry and molecular biology are composed of the main science base of the Biotechnology patents. The Chemistry and Medicine journals like *Journal of Biological Chemistry*, *Journal of Medicinal Chemistry*, *Chemical and Pharmaceutical Bulletin*, and so forth, are the main science base of Pharmaceutical patents. The science base of the patents on the Organic Fine Chemistry mainly comes from those chemistry journals like *Journal of Biological Chemistry*, *Journal of Medicinal Chemistry*, *Tetrahedron Letter*, and so on. Besides the above specialized journals the three multidisciplinary journals, i.e. the *PNAS*, *Science* and *Nature*, are also the knowledge base of the Chinese patents for the three strongly science-based fields, respectively.

Table 9. Top 10 journals ranked by citations in the three strongly science-based fields, respectively

Biotechnology		Pharmaceutical		Organic Fine Chemistry	
Journal	Citations	Journal	Citations	Journal	Citations
PNAS	28	*J. Biol. Chem.*	30	*J. Biol. Chem.*	26
J. Biol. Chem.	26	*PNAS*	26	*PNAS*	23
Science	17	*J. Med. Chem.*	21	*J. Med. Chem.*	19
Nucleic Acids Res.	12	*Science*	18	*Tetrahedron Lett.*	18
Nature	12	*Chem. Pharm. Bull.*	15	*Science*	17
Gene	11	*Nature*	14	*J. Org. Chem.*	17
Cell	9	*BMCL*	14	*Nature*	15
Biotechniques	9	*J. Org. Chem.*	14	*Cancer*	12
Eur. J. Biochem.	8	*BBRC*	14	*J. Am. Chem. Soc.*	12
Biochemistry	8	*Cancer Res.*	14	*BMCL*	11

Like Figure 2, using Pajek we can visualize the co-citation patterns of patents in the three strongly science-based fields, respectively. Here the corresponding figures are omitted for simplicity. We find that co-citation patterns in patents are different depending on the knowledge base of the fields. For Biotechnology the *PNAS* is central in relating to other journals. The width of the line between the *PNAS* and the *Science* is the thickest, so the link strength between them is highest with a value of 15. The *Nucleic Acids Research* and the *PNAS* has the second highest value of 9, tied with the *Nature* and the *PNAS*. For the field of Pharmaceutical, the strongest linked-journals are the *Journal of Biological Chemistry* and the *PNAS* with a score of 18. The *PNAS* and the *Science* follow with a slightly lower value of 16. There are four pairs among those journals with tied values of 12, taken the third position. In addition, the link strength of the network for the Pharmaceutical is relatively equally distributed as compared with the Biotechnology. For the Organic Fine Chemistry the link between the *PNAS* and *Science* has the highest value of 14 with a thickest width of the line. The second place is tied by two groups of lines, namely the *Journal of Biological Chemistry* vs. the *PNAS* as well as the *Cancer* vs. the *Cancer Research*, with a score of 12.

Conclusions

Science and technology are closely connected, interacting and interdependent. It is a complex job to get a comprehensive picture of the science-technology interplay. In this paper, we tried to apply social network analysis in describing the characteristics of the networks of scientific journals, resulting from the Chinese patent data of United States Patent and Trademark Office (USPTO). We mined the Chinese patent data granted by USPTO during 1995–2002, and extracted the information of SCI journals from the NPRs of the patent data. We then constructed the networks of journals. However, unlike previous studies, we paid more attention to the characteristics of the networks for journals, by using the social network analysis from the global and the ego views, respectively. In a sense, this paper may be another exploration of the interaction between science and technology in China.

The networks of journals in all fields, the three strongly science-based fields (i.e. Biotechnology, Pharmaceuticals, and Organic Fine Chemistry), and the three weakly science-based fields (i.e. Optics, Telecommunications, and Consumer Electronics), have been analyzed, by using the approach of social network analysis. We found a number of interesting properties of these networks as follows.

From the global view, the large giant components with more than 90% of total size of the network exist in the networks for all fields and for the three strongly science-based fields. It indicates that in these networks, vast majority of journals are connected via knowledge relations. Besides, the average distance between all pairs of journals, in which a connection exists, is all less than 3, even for such large networks as all fields and those strongly science-based fields. Also, in terms of the average degree, the network of the Pharmaceutical has the highest, followed by the Organic Fine Chemistry. As for another structure measure: clustering coefficient, each of networks for all fields and for the strong science-based fields possesses much lower value than weakly science-based networks. Using the three centralization measures for networks, we also found that the network for the Biotechnology is the most centralized in all networks while the network for Telecommunication is the least.

From the ego view, we found the three famous multidisciplinary journals, namely the *PNAS*, the *Science* and the *Nature,* share the most prominent position in the network of all fields, no matter which of the three centrality measures is used. The similar finding can be seen in the network of the Organic Fine Chemistry. As for the network of the Biotechnology, the *PNAS* and the *Science* still remain their leading positions under the three centrality measures. Regarding to the network of Pharmaceutical, the *PNAS* has the highest centrality at global level, no matter which of the indicators is concerned; Two chemistry journals: the *Journal of Medicinal Chemistry* and the *Chemical and Pharmaceutical Bulletin* also take the better positions while the *Nature* is ranked in the middle or on the bottom of the list in terms of these three centrality measures. More surprisingly, except in the field of Biotechnology, the most frequently cited journals by patents do not always take the better positions when ranked by the three centrality measures. It should be pointed out that any of these indicators could not be belittled, and these measures may indicate different dimensions. The three centrality measures just provide us with a measure of importance of the actors at the level of overall network. In addition, the distribution of the betweenness centrality is skewer than those of other centrality measures, and only a few journals have higher values of betweenness centrality. No matter any of networks is concerned, the *PANS* always has a higher value of betweenness, which maybe highlight the fact that the betweenness centrality is an indicator of the interdisciplinarity of journals presented by LEYDESDORFF [2007A]. In one word, it shows that patents of different fields have different knowledge base, composed of various specialized journals and the three famous multidisciplinary journals, i.e. the *PNAS*, *Science*, and *Nature*. Besides, no matter which of fields studied here, the three journals, i.e. *PNAS*, *Science*, and *Nature*, are read most frequently by patent inventors and examiners.

However interestingly, these conclusions are little more than a good start. First and foremost, we need to take the domestic patents granted by State Intellectual Property Office of the People's Republic of China (SIPOPRC) into consideration. For one thing, the Chinese US patents are far less than domestic patents. For the other thing, the size of the networks studied here are by and large smaller than other social network like scientific collaboration networks, metabolic networks, movie actors collaboration networks, and so on. The relatively small size of networks studied here may gives some influence to the statistical significance of our results.

Second, some earlier studies have shown that the scientific references, particularly the SCI covered publications, can not provide an accurate representation of the interactions between science and technology because of the existence of tacit knowledge [TIJSSEN & AL., 2000; BHATTACHARYA & MEYER, 2003]. Besides, patent citation includes various types of documents such as journals papers, conference papers, text books, and so forth. In this paper, only the SCI covered papers are involved. More precisely, we only take the SCI journals as the providers of science base for the Chinese patent. Therefore, the SCI journals provide only limited evidence about to what extent the knowledge can act as important base for the technology improvement. Journals coming from other type of references should be included in the future analysis.

Third, due to the limitation of databases we access, the name changes for some journals can not be checked. So, in our journals databases, there are inevitably the same journals, but with two or more different names. Nevertheless, these small proportion of journals have a slightly impact on the results because the approach of social network analysis focus on the relationships between the actors.

Fourth, in this paper the US patent data for China are from 1995 to 2002, and not normalized like Leydesdorff's cases [LEYDESDORFF, 2004, 2007A. 2007B]. More of the structure might be seen by normalizing the data using, for example, the cosine. The predominant position of the three leading journals (*Science*, *Nature*, and *PNAS*) is then probably reduced and other conclusions are made possible when using the vector space. In the further researches we will extend the time span of the data set, such as 1995–2005, and normalize the data to draw more of interesting conclusions.

Finally, we need to produce data-sets for other countries other than China. It is interesting to identify the differences and the similarities of journal networks between China and other countries. These are all future research directions, in which we should go step by step on the basis of more powerful databases and the methodology presented in the study.

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