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Assessing the industrial opportunity of academic research with patent relatedness: A case study on polymer electrolyte fuel cells

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A B S T R A C T

The detection of promising academic research is vital for firms in a variety of sectors. Bibliometric tools can be used to detect such research in the midst of a pile of papers and patents; however, the relationship between academic research and industrial technology development has not been well documented. In this paper, we introduced patent relatedness, which measures the semantic similarity of papers and patents, and conducted a case study on polymer electrolyte fuel cells (PEFC). The results show that in an academic research area with a small number of papers, recent average publication year, low patent relatedness has a high potential to increase in subsequent years. Research areas are identified by clustering the citation network of academic papers, and their patent relatedness and time series variation were measured and analyzed. Our results showed that potential research areas were characterized by small but emerging features. Using these findings, we identified the potential PEFC research areas and the research capability of each country.

1. Introduction

The demand for innovation to overcome problems such as the dearth of food in developing countries, water shortages, and growing global energy requirements has drawn increasing attention. Academic research is expected to provide fundamental solutions, and its importance is well recognized. A previous study claims that 10% of new products and processes are from academic research [1]. Therefore, the identification of potential academic research areas, which can produce key technologies in industry, has been one of the major challenges in technology and innovation management literature [2–6].

However, this does not mean that all academic research areas will lead to the advancement of industrial technologies. A prior concern of academic research has been to explain unknown phenomena and mechanisms rather than to produce new products and services. The latter are certainly the outcome of academic research, but not its prior aim in most cases. It is also known that although academic research leads to various seeds of innovation, it takes years for this innovation to come to market and be commercialized due to various obstacles. For example, if a new material is found with a promising chemical property, it might also have a low physical property and a low throughput of the manufacturing process. Therefore, the assessment of academic research areas in term of potential for industrial application is a difficult task.

Another practical difficulty arises from the fact that the number of research papers and patents have increased to the point that they cannot all be read manually. It has been stressed that society is currently experiencing an excess of publications [7]. A recent observation reports that review papers and meta-analysis papers have more citation impact than standard articles, which reflects the problem of excessive publications [8]. Although strategic decisions on research and development

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(R&D) should be made after observing and analyzing global R&D trends by reading research papers or patents [2], there is a tendency to miss emerging and potential research areas because of the flood of publications. It brings the risk that R&D will miss potential emerging research areas. Traditional approaches such as reviewing papers and assessing international patent classification trends are still useful in providing a brief overview of a research area. However, these approaches face a fundamental difficulty in keeping up with the rapid pace of development and the moving target of technology.

Bibliometrics has been developed to overcome the above difficulties. In bibliometrics, citation network analysis is an effective way to identify emerging academic research clusters and analyze the characteristics of each cluster without reviewing papers one by one [5,9–12]. For example, citation network analysis has been used to confirm the rapid growth of fuel cell and solar cell technology research in the field of energy research [5]. Ho et al. (2013) applied citation network analysis to research trends and the development path of fuel cell technology [11]. Citation network analysis is also used for mutually influential biofuel research topics [12]. Other researchers have used journal citation data and journal classification data to describe the network of energy-related journals [13,14]. In addition to network analysis, text analysis is used to consider multi-word phrase frequencies and phrase proximities and to extract the taxonomic structure of energy research [15,16].

However, the detection of emerging clusters in academic research is not enough to utilize the results for R&D strategic planning, because academic research does not always aim to develop industrial technology as mentioned before. On the other hand, patent analysis can directly identify present situation of industries, which complement the analysis of academic papers. Daim et al. suggested a forecasting method using bibliometrics and patent analysis [17]. As for energy-related technology, Woon et al. utilized bibliometrics and distributed generation to highlight key trends in related technological developments [18]. Verspagen explained the development trajectory of fuel cell technologies by patent citation networks [19]. However, emerging technology clusters identified from patent analysis seem to be obtained too late to adopt as R&D targets for firms because the technologies included in patent analysis have already been patented.

An alternative approach is to integrate paper analysis with patent analysis. A previous paper reported that the R&D stages of basic research, applied research, development, application, and social impact can be represented by different bibliometric data including papers, patents, newspapers, business, and popular press, respectively [20,21]. In respect to these R&D stages, Martino stated that by "observing a technological innovation at an early stage in this sequence, it may be possible to anticipate when it will reach later stages in the sequence, or at least provide warning that further developments may follow" [21]. Recently, Shibata et al. proposed and demonstrated a bibliometric approach using paper and patent analysis to detect the commercialization gap between academic papers and patents [22]. This approach can detect the academic research area, which has not been patented yet and is the chance for firms to participate in. Later, Leydesdorff et al. renamed this approach as "innovation opportunities explorer" [23].

These methods are beneficial for R&D management to determine the fundamental direction of strategies, but are not sufficient to evaluate specific and potential research areas. Although previous studies have shown the possibility of identifying promising candidates for academic research for future industry applications, we still cannot determine the exact focus of such research with bibliometrics.

In this paper, we introduce a parameter, "patent relatedness," which measures keyword relatedness between patents and academic research clusters. Patent relatedness can be measured in each research cluster, focusing on a specific technology. Hence, we can evaluate the potential of a specific technology using patent relatedness. A case study is done on polymer electrolyte fuel cells (PEFC), which is a major research field in fuel cells. Patent relatedness was applied to assess whether the focal technology in a PEFC research cluster is near commercialization or not. Low patent relatedness of a research cluster means that technologies in the research area have not yet been frequently patented. Additionally, a research cluster with low patent relatedness has many opportunities and allows companies to obtain patents of that technology. Of course, academic research clusters, which will not be commercialized in the long term, are meaningless for industry. Therefore, we analyze the features of research clusters which have low patent relatedness in the analyzed period but will obtain high patent relatedness hereafter. In this paper, we define such clusters as potential research clusters. We determine the features of potential research clusters by determining the parameters relevant to patent relatedness by analyzing several research clusters in time series about PEFC technology. Based on the findings, the future potential PEFC research clusters are identified and reported.

2. Data and methodology

2.1. Data

PEFC is an important technology for reducing energy consumption because of its high energy conversion efficiency. We collected bibliographic data from academic publications on fuel cells. Data for academic papers, including the title, author, publication year, abstract, address, and reference were retrieved from the Science Citation Index Expanded (SCI-EXPANDED), compiled by the Institute for Scientific Information (ISI), Thomson Reuters. The bibliographic data of patents were collected from Derwent enhanced database, Derwent World Patents Index (DWPI), through Thomson Innovation by Thomson Reuters. All patents in the DWPI (data since 1962 as publication year) were collected. We use the same query, "fuel cell*," to collect data from papers and patents. Data collection was done in October 2012. We used Derwent enhanced data with translations to retrieve patents. Patent family was merged and regarded as one node in the network. Application year is used to differentiate the year of the patents. The papers and patents related to PEFC were identified by fuel cell clustering, which is explained in the following section. This is necessary because we collect papers via a simple query, "fuel cell*", and our collected dataset includes papers on other types of fuel cell technologies. When these different types are included in the analysis, interpreting the results becomes complex. Therefore, in this paper, we focus only on PEFC. One plausible approach to collecting only PEFC papers would be to replace the query,

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"fuel cell*," with "PEFC," but in this case, the query becomes too specific to include the variety of technologies relating to PEFC that do not include "PEFC" in their bibliographic records. The corpus-building strategy adopted in this paper might distort the results, but we disregard the bias and adopt this corpus for PEFC data. We consider that the bias can be disregarded because in this paper, we compare the research clusters of papers and patents, and the bias effect is considered to be uniform among research clusters.

2.2. Methodology

Our methodology is schematically shown in Fig. 1. In step (1), the data from academic papers were downloaded. Subsequently, as step (2), we constructed citation networks by regarding papers as nodes and intercitations as links. The network created in each year facilitates the time-series analysis of the citation networks. According to a previous study, intercitation, which is also known as direct citation, is the best of approaches tested to detect emerging trends [24]. In network analysis, only the data for the largest graph component were used, and we eliminated those not linked with any other papers in step (3). After extracting the largest connected component, in step (4), the network was divided into clusters using the topological clustering method of Newman's algorithm, which extracts tightly knit groups of nodes [25]. Newman's algorithm employs the following equation:

$$Q = \sum_{s=1}^{M}\left[\frac{l_s}{l} - \left(\frac{d_s}{2l}\right)^2\right] \tag{1}$$

where Q is the independence of module, M is the number of clusters, s is the cluster, l is the number of links in whole network, l_s is the number of links in cluster s, d_s is the sum of links in the cluster s, respectively. In Newman's algorithm, the clusters are divided into subgroups to maximize Q. Eq. (1) means the sum of "the probability that reference links exists within the cluster s, subtracted by the probability of random link. This algorithm leads well-separated clusters in terms of research area. This method has been utilized for many research fields and successfully obtained clusters, separated in each research filed [5,9–12]. We analyzed the characteristics of clusters, including the average publication year of papers, the number of papers, and the dominant country in each cluster. After clustering the maximum connected component, we obtained clusters that included PEFC, solid oxide fuel cell (SOFC), and bio fuel cells. Then, we extracted the clusters focusing on PEFC from among the above fuel cell technologies.

In step (5), the PEFC clusters extracted in step (4) were recursively clustered by Newman's algorithm. Recursive clustering can provide subclusters, enabling us to determine the details of PEFC technology. Characteristics of subclusters such as the average publication year and dominant country were also analyzed.

Finally, in step (6), the "patent relatedness" of each cluster was calculated. The calculation of patent relatedness was performed by the cosine similarity of the term frequency–inverse document frequency (tfidf) vector, which is the best of approaches tested for discovering corresponding relationships between papers and patents [26]. Eq. (2) of the cosine similarity, Cosine (s,t), between academic research cluster s and patent data t is defined with the term frequency weighting factor, $FreW$, as

$$\mathrm{Cosine}(s,t) = \frac{\sum \overrightarrow{FreW_{si}} \times \overrightarrow{FreW_{ti}}}{\sqrt{\left(\sum \overrightarrow{FreW_{si}}\right)^2}\sqrt{\left(\sum \overrightarrow{FreW_{ti}}\right)^2}}, \tag{2}$$

where

$$FreW_{si} = \frac{n_{si}}{n_s} \times \log\left(\frac{N_s}{N_i}\right), \tag{3}$$

$$FreW_{ti} = \frac{n_{ti}}{n_t} \times \log\left(\frac{N_t}{N_i}\right), \tag{4}$$

i is the term, s is the cluster, and t is the patent dataset. n_{si} and n_{ti} are the number of occurrences of term i in cluster s and that in the patent dataset, respectively. n_s and n_t are the total number of terms in cluster s and that in the patent dataset, respectively. N_s and N_t are the total number of documents in cluster s and the patent dataset, respectively. N_i is the number of documents containing term i in cluster s or the patent dataset.

The above steps were applied for the data published until 2006, 2008, 2010, and 2012 to trace the dynamic change of patent relatedness in the timeline (Fig. 2). The patent relatedness of each cluster was calculated with the patent data published in the year corresponding to the data of the academic papers used in the calculation. The numbers of papers published until 2006, 2008, 2010, and 2012 collected by the query "fuel cell*" are 16,857, 25,090, 35,519, and 46,989, respectively. The numbers of papers in the PEFC cluster until 2006, 2008, 2010, and 2012 are 6193, 11,294, 15,877, and 22,047, respectively. The number of clusters included in this analysis is 64, which is the number of major clusters in 2006; those clusters are tracked to monitor their growth in the academic citation network and to measure the patent relatedness change. Four points in the timeline were sufficient to reasonably extract the tendencies of patent relatedness, as shown in the results. We tracked the growth

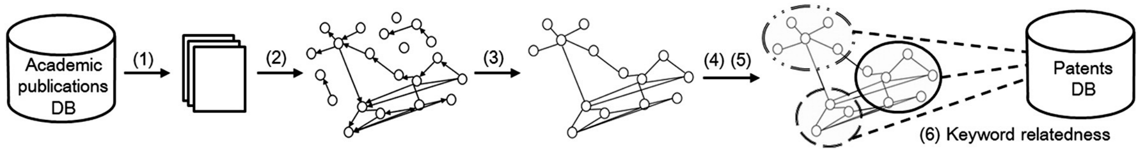

Fig. 1. Schematic illustration of clustering and measurement of patent relatedness.

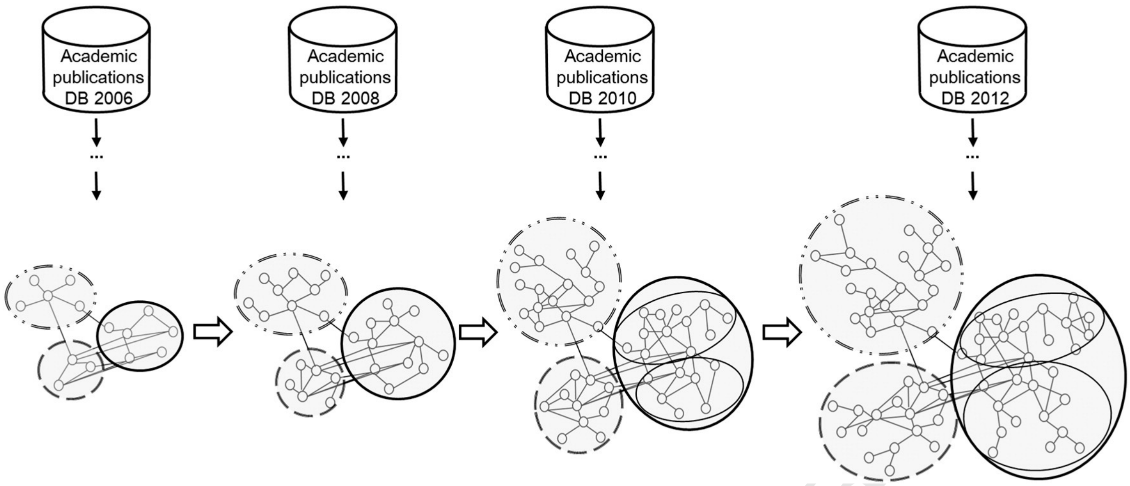

Fig. 2. Development of clusters and the tracking of their growth.

of each subcluster in terms of PEFC and measured the patent relatedness. To analyze the tendency of patent relatedness change, we use the gradient of patent relatedness (GPR) as a parameter. GPR was calculated by following equation;

$$GPR = \frac{4\sum_{y=2006}^{2012} P_y y - \sum_{y=2006}^{2012} P_y \sum_{y=2006}^{2012} y}{4\sum_{y=2006}^{2012} P_y^2 - \left(\sum_{y=2006}^{2012} P_y\right)^2} \qquad (5)$$

where y is year ($y = 2006, 2008, 2010, 2012$), P_y is the patent relatedness of a subcluster in the period of y, respectively. Eq. (5) means that GPR is the gradient of the linear function of patent relatedness against year, derived from least squares. It has been noted that patent relatedness grows in the timeline (GPR > 0), which means that PEFC technology is being patented.

To track the growth of subclusters, we must identify the subsequent cluster in each year. Here, we assume the subsequent cluster in the next time period as the cluster that shared the same core papers in the citation network and the same technological terms in the original cluster. In some cases, one cluster was divided into several subclusters, as illustrated by a cluster encircled by a solid line in Fig. 2. Divided clusters were summed up as one cluster to calculate patent relatedness and to extract the tendencies of patent relatedness change.

3. Results & discussion

In Figs. 3–5, we analyzed the patent relatedness tendencies of PEFC research clusters. The averages of patent relatedness in 2006, 2008, 2010, and 2012 are 0.00437, 0.00476, 0.00566, and 0.00583, respectively. This overall increasing trend of patent relatedness reflects the growing industry concern about PEFC. However, even in PEFC, there is a variety of trends at the subcluster level; these will be analyzed below. The patent relatedness of some clusters is larger than those averages, which means that the technology corresponding to such clusters is already well patented. Some are below those averages, which means that the technology has not been extensively patented. The latter case has the potential for industry to conduct R&D and focus on patent application in this field, although investment in such a basic research area might be risky. Then, we need to select the research area that will be patented in future. The analysis of GPR can meet this requirement.

The GPR of each cluster was plotted against the patent relatedness in 2006, which is the starting year of our analysis (Fig. 3), the publication year (Fig. 4), and the number of papers in 2006 (Fig. 5).

As shown in Fig. 3, clusters with lower patent relatedness in 2006 have higher GPR values in subsequent years. This is because technology that was well patented in previous years has less of a tendency to be patented later (P value of these parameters is 1.35×10^{-5}). Technological fields where many patents have already been issued have low attractiveness for industry to pursue further inventions. When patent relatedness in 2006 is below 0.005, the GPR seems to become high. The value of this boundary line, that is, a GPR of 0.0005, can indicate whether the cluster will become well patented in the immediate future or not. Therefore, we consider clusters with

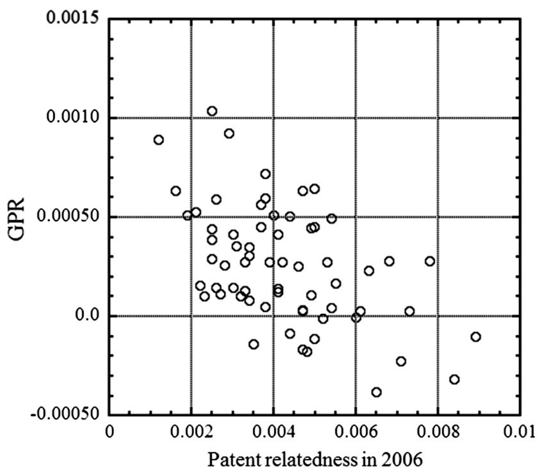

Fig. 3. GPR and patent relatedness in 2006.

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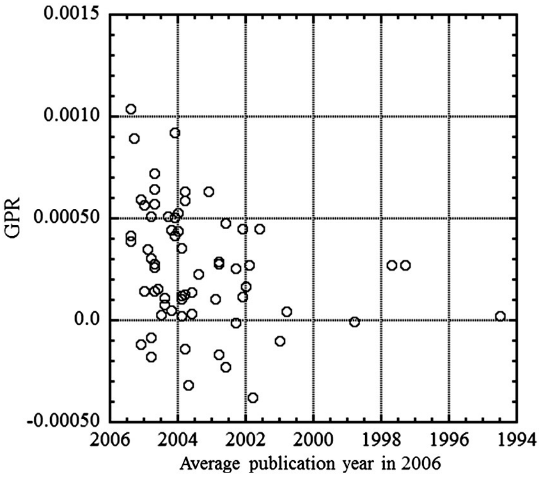

Fig. 4. GPR and average publication year of papers in 2006.

GPR values greater than 0.0005 to be potential research clusters.

Fig. 4 shows that the GPR becomes high when the average publication year is more recent (P value of these parameters is 0.0319). This indicates that an emerging academic research cluster is promising for industry and will be patented in subsequent years. In particular, when the average publication year of papers in each cluster in 2006 is more recent than 2003, the GPR becomes large, while there is a large variance in their GPR values. The difference between 2003 and the year of the data in this case, 2006, is three years. Thus, a potential research cluster should be of more recent origin than three years from the present.

Fig. 5 plots the cluster size, that is, the number of papers in each cluster in 2006, and the GPR. A smaller number of papers in a cluster in 2006 leads to a higher GPR value, which may have less relevance with GPR than other parameters (P value of these parameters is 0.141). When the cluster size is below 70, the GPR seems to become high.

The relationship among three parameters—patent relatedness, average publication year, and the number of papers in 2006—is shown in Fig. 6. In general, these parameters have a relationship such that as a cluster has a smaller number of papers, it also has lower patent relatedness and a more recent average publication year. However, in contrast to the overall tendency of the relationship, some clusters have low patent relatedness but an older average publication year. Therefore, we can conclude that a potential research area must have at least the following three characteristics: a cluster with lower patent relatedness than 0.005, an average publication year more recent than 3 years from the present, and a smaller number of papers than 70. Although these are not precise values, based on the assumption that potential research has a higher GPR than 0.0005, we can consider them to be rough indicators. However, not all clusters with a low GPR were excluded based on these three values.

In Table 1, according to the key features derived in the previous section, we extracted 16 potential research clusters in 2012 where patent relatedness is expected to increase. *Cluster name* indicates a specific subject targeted by the paper in each cluster. *Dominant country* indicates the country that published the largest number of papers or exceeds half of the number of papers for each cluster; close attention should be paid to this indicator. The research area actively studied in the home country provides the opportunity for a firm to participate easily in the research area because the company can engage in collaborative research while making profits in its geographic location. In addition, information about the research area that is actively studied abroad enables us to avoid overlooking seeds of technology that are emerging in other countries. The potential research clusters shown in Table 1 are composed of nine clusters related to catalysts, five related to polymer electrolytes, and two to other subjects.

As we can see in Table 1, academic research investigates catalysts and their properties. Catalysts utilized for various fuels, such as methanol and ethanol, are specifically focused on; these liquid fuels are preferable for portable energy sources because of their high energy density. However, these liquid fuels generally do not have enough reactivity with the

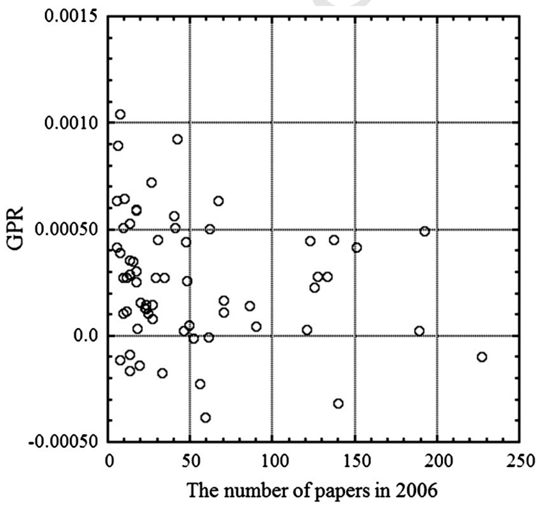

Fig. 5. GPR and cluster size in 2006.

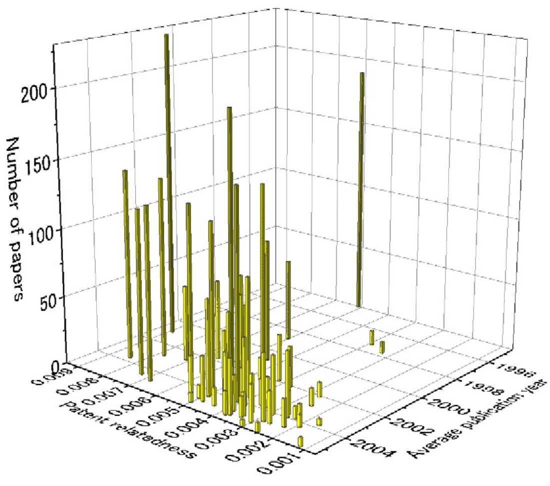

Fig. 6. Relationships among three parameters: patent relatedness, average publication year, and number of papers in each cluster in 2006.

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Table 1
Potential research clusters in 2012.

Subject	Cluster name	Average publication year	Number of papers	Patent relatedness	Dominant country
Catalyst	PtPd-based catalyst on carbon for methanol and ethanol oxidation	2009.3	53	0.0034	PR China
	Catalytic properties of tantalum-carbide-nitride	2009.6	49	0.0034	Japan
	Pt-based catalysts for direct ethylene glycol fuel cell	2009.8	64	0.0031	USA, Brazil, PR China, France, Italy
	PtRu catalyst on functionalized multi-walled carbon nanotube for direct methanol fuel cell	2010.0	36	0.0026	PR China
	Catalytic properties of nanoparticles of ternary Pt based catalysts (PtNiCo, PtVFe, etc.)	2010.0	42	0.0032	PR China
	Catalytic properties of manganese oxides on carbon for the oxygen reduction reaction in alkaline media	2010.1	39	0.0032	PR China, USA, Brazil, England, France
	Pt nanoparticles on carbon nanotube by a plasma treatment	2010.3	26	0.0024	PR China
	Catalytic properties of Ag nanoparticles on carbon for oxygen reduction reaction in alkaline media	2010.8	25	0.0025	PR China
	Co-based catalyst on graphene for oxygen reduction reaction in alkaline media	2011.0	20	0.0024	PR China, USA
Electrolyte	Multiblock copolymer with sulfonated pendant as polyelectrolyte membranes	2009.1	47	0.0036	PR China, Japan
	Proton conductivity of sulfonic acid or imidazole functionalized mesoporous material (mainly Si-MCM-41)	2009.2	31	0.0024	Germany
	Nafion + functionalized montmorillonite composite as polyelectrolyte membranes for direct methanol fuel cell	2009.3	24	0.0029	Iran, USA
	Proton-conducting membranes containing ionic liquid as polyelectrolyte membranes	2009.7	65	0.0036	PR China, Japan
	Proton conductivity of polybenzimidazole + inorganic particles for high temperature PEFC	2010.2	19	0.0030	England, PR China
Others	Degradation study of elastomeric gasket materials	2009.3	24	0.0024	USA, PR China
	Hydrogen generation from aluminum for fuel cell application	2009.5	59	0.0039	PR China, USA

present catalyst, platinum. Additionally, non-platinum catalysts or platinum alloys that include a low percentage of platinum are also attractive because the high cost of platinum is one of the factors that have hampered PEFC commercialization. Although several alloys are investigated for our above purpose, the nine research areas shown in Table 1 are promising, and they include much room for firms to develop and apply patents.

Polymer electrolytes are another R&D candidate for firms. Polymer electrolytes allow protons to pass but not electricity and fuel. The desired properties of an electrolyte membrane are mechanical and chemical stability, low fuel crossover, and high proton conductivity. Nafion, the most general electrolyte membrane for PEFC, has good mechanical and chemical stability, low fuel crossover for hydrogen, and high proton conductivity at high relative humidity conditions. However, the proton conductivity of Nafion severely decreases at low humidity conditions, which requires water management. This water management leads to a high price and reduced energy efficiency. Moreover, Nafion allows fuels with an affinity for water, such as methanol, to pass. The solutions are, for example, a synthesis of a novel polymer electrolyte, and a composite of a polymer electrolyte and inorganic particles. The five research areas shown in Table 1 seem to be attractive for firms to apply for patents.

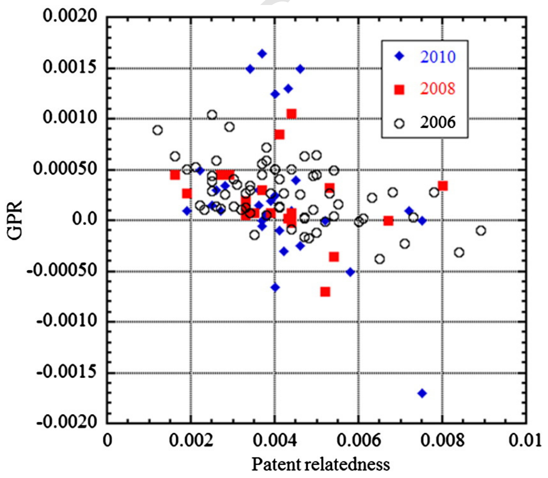

Fig. 7. The relation between GPR and the number of papers in the year the cluster is derived.

In this paper, we analyzed changes in patent relatedness. However, the approach adopted in this paper has the following limitation. In this paper, we tracked the change of patent relatedness by monitoring the GPR and fixing our unit of analysis as clusters in 2006. In some cases, clusters in 2006 were divided into two clusters after clustering in subsequent years. In our analysis, we integrated them and regarded each as one research cluster, measuring the GPR of these synthesized clusters. In doing so, we may have missed a dynamic change of citation networks. Clustered network structures are not static, but change in real time. Therefore, if we treat these divided clusters as different research clusters, various other features and implications might be obtained. Fig. 7 shows the result when we treat the divided clusters in 2008 and 2010 as independent (P value are 0.298 and 0.0588, respectively). Patent relatedness is calculated for each year. GPR is not calculated for clusters divided at 2012 because it requires at least two points. The data for 2006 are as shown in Fig. 3. As can be seen, the tendency of the GPR affected by patent relatedness seems to be enhanced if we regard divided clusters in

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subsequent years as different clusters. In addition, as can be seen in Fig. 7, five clusters derived in 2010 have a distinctively high GPR. Although we cannot derive conclusive results yet, analysis that includes the dynamic evolution of clustered citation networks may be able to extract potential research clusters in an efficient and effective way. This should be investigated in future works.

4. Conclusion

Key features of potential technological research areas were analyzed. In this paper, we defined a potential research area as one where patenting is not currently being done, but will be in the future. We introduced a parameter, patent relatedness, in order to assess such features. Our case study on PEFC, which measured patent relatedness change from 2006 to 2012, revealed three characteristics for potential research clusters: lower patent relatedness than 0.005, a more recent average publication year than 3 years from the present, and a smaller number of papers than 70. These values are not thresholds and are not quantitatively precise, but we can utilize the results as a guideline to select R&D targets. Based on these key features, we identified 16 potential research clusters for 2012, including 9 clusters on catalysts for oxygen reduction reactions, 5 clusters on polymer electrolytes, and 2 on other subjects. Our approach can be used to extract attractive academic research areas from a body of publications in an efficient manner. Further study is needed to explore the dynamic and complex change of citation networks, and to test the accuracy to estimate the patented extent in a research area. Further work is also needed in other research domains to test the relevance of our hypothesis derived in this paper. Above all, the usefulness of the results should be tested in practice with a survey or project in enterprises.

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References

[1] E. Mansfield, Academic research and industrial innovation, Res. Policy 20 (1) (1991) 12.

[2] L. Leydesdorff, S. Cozzens, P. Van den Besselaar, Tracking areas of strategic importance using scientometric mappings, Res. Policy 23 (1994) 217–229.

[3] R.N. Kostoff, R.R. Schaller, Science and technology roadmaps, IEEE Trans. Eng. Manag. 48 (2001) 132–143.

[4] R.N. Kostoff, Literature-related discovery (LRD): introduction and background, Technol. Forecast. Soc. Chang. 75 (2) (2008) 165–185.

[5] Y. Kajikawa, J. Yoshikawa, Y. Takeda, K. Matsushima, Tracking emerging technologies in energy research: toward a road map for sustainable energy, Technol. Forecast. Soc. Chang. 75 (6) (2008) 771–782.

[6] N. Shibata, Y. Kajikawa, Y. Takeda, K. Matsushima, Detecting emerging research fronts based on topological measures in citation networks of scientific publications, Technovation 28 (2008) 758–775.

[7] G.S. Davidson, B. Hendrickson, D.K. Johnson, C.E. Meyers, B.N. Wylie, Knowledge mining with VxInsight: discovery through interaction, J. Intell. Inf. Syst. 11 (1998) 259–285.

[8] M. Barrios, G. Guilera, J. Gómez-Benito, Impact and structural features of meta-analytical studies, standard articles and reviews in psychology: similarities and differences, J. Informetrics 7 (2013) 478–486.

[9] H. Small, Tracking and predicting growth areas in science, Scientometrics 68 (2006) 595–610.

[10] N. Shibata, Y. Kajikawa, I. Sakata, Detecting potential technological fronts by comparing scientific papers and patents, Foresight 13 (2011) 51–60.

[11] J.C. Ho, E.C. Sawa, L.Y.Y. Lua, J.S. Liu, Technological barriers and research trends in fuel cell technologies: a citation network analysis, Technol. Forecast. Soc. Chang. (2014) (in press).

[12] Y. Kajikawa, Y. Takeda, Structure of research on biomass and bio-fuels: a citation-based approach, Technol. Forecast. Soc. Chang. 75 (2008) 1349–1359.

[13] R. Dalpé, F. Anderson, National priorities in academic research—strategic research and contracts in renewable energies, Res. Policy 24 (1995) 563–581.

[14] R.J.W. Tijssen, A quantitative assessment of interdisciplinary structures in science and technology: co-classification analysis of energy research, Res. Policy 21 (1992) 27–44.

[15] 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.

[16] 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.

[17] T.U. Daim, G. Rueda, H. Martin, P. Gerdsri, Forecasting emerging technologies: use of bibliometrics and patent analysis, Technol. Forecast. Soc. Chang. 73 (2006) 981–1012.

[18] W.L. Woon, H. Zeineldin, S. Madnick, Bibliometric analysis of distributed generation, Technol. Forecast. Soc. Chang. 78 (2011) 408–420.

[19] B. Verspagen, Mapping technological trajectories as patent citation networks: a study on the history of fuel cell research, Adv. Complex Syst. 10 (2007) 93–115.

[20] R.J. Watts, A.L. Porter, Innovation forecasting, Technol. Forecast. Soc. Chang. 56 (1997) 25–47.

[21] J.P. Martino, A review of selected recent advances in technological forecasting, Technol. Forecast. Soc. Chang. 70 (2003) 719–733.

[22] N. Shibata, Y. Kajikawa, I. Sakata, Extracting the commercialization gap between science and technology case—study of a solar cell, Technol. Forecast. Soc. Chang. 77 (2010) 1147–1155.

[23] L. Leydesdorff, D. Rotolo, W. de Nooy, Innovation as a nonlinear process, the scientometric perspective, and the specification of an 'innovation opportunities explorer', Technol. Anal. Strateg. Manage. 25 (2013) 641–653.

[24] N. Shibata, Y. Kajikawa, Y. Takeda, K. Matsushima, Comparative study on methods of detecting research fronts using different types of citation, J. Am. Soc. Inf. Sci. Technol. 60 (2009) 571–580.

[25] M.E.J. Newman, Fast algorithm for detecting community structure in networks, Phys. Rev. E. 69 (2004) 066133.

[26] N. Shibata, Y. Kajikawa, I. Sakata, Measuring relatedness between communities in a citation network, J. Am. Soc. Inf. Sci. Technol. 62 (2011) 1360–1369.

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