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A METHODOLOGY FOR IDENTIFYING CORE TECHNOLOGIES BASED ON TECHNOLOGICAL CROSS-IMPACT: ASSOCIATION RULE MINING AND ANP APPROACH

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Abstract

There have been attempts to examine technological structure and linkage as technological impact. Cross-impact analysis (CIA) has been mainly employed with cross-impact index to identify core technologies. Cross-impact index, however, cannot successfully capture the overall relationship based on the impacts among technologies. Furthermore, it is a time-consuming task to calculate all cross-impact index especially based on patents without developing computer program. To address this limitation, this study suggests new approach to identify core technologies in technological cross-impact interrelationship. Specially, the approach applied data mining technique and multi-criteria decision making (MCDM) method to the co-classification information of registered patents. At first, technological cross-impact matrix is constructed with the confidence values by applying association rule mining (ARM) to the co-classification information of patents. Then, Analytic Hierarchical Process (ANP), one of MCDM methods, is employed to the constructed matrix for identifying core technologies from the perspectives of overall cross-impacts. A case study of telecommunication technology is conducted to illustrate the process of executing and utilizing the proposed approach. It is expected that suggested approach could help technology planners to formulate strategy and policy for technological innovation.

Keywords: Cross Impact Analysis (CIA), Association Rule Mining (ARM), Analytic Network Process (ANP), Core Technology, Patent Co-classification

Introduction

The characteristics of modern technology change can be defined as complexity and radicalness. Under this environment, the grasping of technological trend and development by analyzing overall structure of technologies and interaction among them has become more important. With this activity, firms can manage R&D portfolio efficiently thus competitive advantage can be gained and sustained [1]. Consequently, there have often been attempts to identify technological structure and relationship.

The core of the identification of technological structure and relationship is the patent analysis [2]. It is reported that patents contain about 80% of all technological knowledge [3] and they can be easily accessed and analyzed through various types of public or private database. Patents are, hence, perceived as useful information for techno-economic analysis and R&D management [4] and a lot of studies have attempted to analyze technological relationship with patent information.

The most commonly used information for analyzing technological relationship with patents is citation. The basic assumption of citation analysis is that the knowledge of cited patent is transferred to citing patent and there exists a technological linkage between them. Citation analysis is a useful index for identifying technological relationship and this can be verified with various studies. [2] [4-18]. However, there are some short comings in the citation analysis. First, the average time-lag between citing-cited patents is over 10 years [19]. Moreover, since citation analysis considers citing-cited relationship between individual patents, it is difficult to identify technological relatedness and characteristics from the perspectives of technological fields [4]. To address this limitation, there have been attempts to applying other information such as co-citation [20] [21], co-word [22], and keyword vector [4]. They also have, however, their own weakness. There is still time-lag problem in co-citation analysis. Co-word analysis and keyword vector analysis requires qualitative judgment and therefore have lack of consistency in the result of analysis. On the contrary, the patent analysis with co-classification information has some advantages compared to above mentioned methods. Co-classification analysis is to analyze technological relationship based on the fact that patents are classified to some technological classes considering their technological characteristics [23]. That is, the assumption which is made is that the frequency by which two classification codes are jointly assigned to the same patent document can be interpreted as a sign of the strength of the knowledge relationship, in terms of knowledge links and spillovers [24]. In contrast with citation analysis, it is based on the hierarchical technological classification system so technological relationship can be analyzed not on the level of individual patents but on the various technological levels according the purpose of studies. Furthermore, error from time-lag is relatively less since patent classification is the information at the time of patent registration. Among the various techniques using the information of patent co-classification, technological cross impact analysis (CIA) has been used as a practical methodology to identify core technology and the interrelationships between technologies by analyzing cross impact between technologies quantitatively based on patent classification data [25]. In patent-based CIA, cross impact index of two technologies is calculated with the probabilities based on the patent co-classification information to analyze the impact between technologies. This is a useful and widely used approach in a patent-based CIA, but it is subject to some limitations. First, it is nearly impossible to construct cross impact matrix without developing computer program because the construction of cross impact matrix requires a huge amount of calculation with patent data. Second, in the identification of core technologies, patent-based CIA does not take into account the overall interrelationships among technologies, only considers the relationships between two technologies.

The main objective of this paper, therefore, is to suggest a new approach to identify core technologies from the perspectives of cross impact based on patent co-classification information considering overall interrelationships among technologies. Specially, the approach applies data mining technique and multi-criteria decision making (MCDM) method. At first, association rule mining (ARM) is employed to calculate technological cross impact index and derive cross impact matrix. Although ARM is one of the representative data mining techniques for exploring vast database, it has rarely been applied to the analysis of patents. Since confidence in ARM is defined as a conditional probability between two technologies and is of the same formula with cross impact index, it is adopted as the index of evaluating technological cross impact. Then, the cross impact matrix is constructed with all calculated cross impact index. Second, ANP (Analytic Network Process), one of the MCDM, is applied to the derived cross impact matrix for identifying core technologies from the perspectives of overall interrelationships among technologies. Since the ANP is capable of measuring the relative importance that captures all the indirect interactions in a network, the derived "limit centrality" indicates the importance of a technology in terms of impacts on other technologies, taking all the direct and indirect influences into account.

The proposed approach is expected to allow technology planners to understand current technological trends and advances by identifying core technologies based on limit centralities. A case stud on telecommunication technologies is presented to illustrate the proposed approach.

Methodological Background

Cross-impact analysis (CIA)

The changing or evolving process of a system could be regarded as a set of some events. Since they interact with each other, the occurrence of a specific event takes an effect on the probability of other events' occurrence. Therefore, it is impractical to forecast the probability of an event's occurrence without considering the occurrence of other events. Like social systems, technological change or progress occurs as a result of the occurrence of various events. For example, the development of mobile phone has to do with that of technologies such as mobile network, memory, and liquid crystal display. When technological events occur through the interactions with each other, an impact of each event of interest on other events is called cross impact [26-28]. Accordingly, CIA has been used as a methodology to forecast the emergence of new technologies and to identify the interrelations between technologies by defining the emergence of new technologies as event occurrences [25].

The general process of CIA is as follows: (1) Define the events to be included in the analysis. (2) Estimate the initial probability of each event. (3) Estimate the conditional probabilities for each event pair. (4) Perform a calibration run of the cross impact matrix. (5) Evaluate the results. In conventional CIA, the step (2) and (3) require the experts' subjective judgment based on their domain knowledge and therefore inconsistent estimates may result. Further, in the step (4), the two kinds of probabilities derived from the former steps should be adjusted because of the intuitive estimation. To overcome these shortcomings of the conventional CIA, Choi et al [25] proposed a patent-based CIA that analyzed cross impact between technologies quantitatively based on patent classification data. In this study, the cross impact of technology 'A' on the technology 'B' is defined as the conditional probability $P(B \mid A) = N(A \cap B) / N(A)$. In this equation, $N(A)$ refers to the total number of patents classified in technology A, and $N(A \cap B)$

indicates the number of patents classified in both technology *A* and *B*.

Association rule mining (ARM)

ARM is one of the data mining techniques to search for interesting relationships among items in large database. Association rule stands for the co-occurrence of two items and indicates that if two items occurs together frequently they have strong association relationship [29]. ARM has mainly been applied to firm activities, especially to marketing [30]. It has also been used to various areas such as bioinfomatics [31] [32], medicine [33], and finance [34].

The three measures of evaluating the rule interestingness are support, confidence, lift and the details of them are described in Table 1. The typical procedure of ARM consists of two steps [35]: (1) Search for frequent itemsets – To create all item combinations over the threshold value of support (2) Generate association rules – To Select itemsets over the threshold value of confidence or lift among the frequent itemsets found in (1). The step (1) is a very time consuming job and the most representative technique for this is Apriori algorithm [36].

Table 1. Measures of interestingness

Measure	Description	Formula
Support	The usefulness of discovered rule $A \rightarrow B$	$P(A \cap B)$
Confidence	The certainty of discovered rule $A \rightarrow B$	$P(B \mid A)$
Lift	The correlation between the occurrence of items in discovered rule $A \rightarrow B$.	$\frac{P(B \mid A)}{P(B)}$

Analytic network process (ANP)

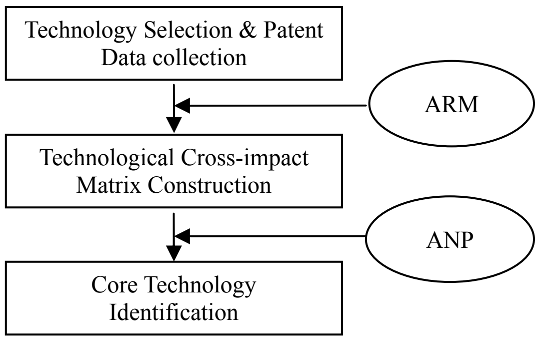
The ANP is a generalization of the AHP which is one of the most widely used MCDM methods [37]. The ANP extends the AHP to problems with dependences and feedback. It allows for more complex interrelationships among decision elements by replacing a hierarchy in the AHP with a network [38]. Therefore, it has been used increasingly in a variety of problems such as project selection [39], product design [40] and development, and financial forecasting [41].

The process of ANP is composed of four steps [37]: (1) Network model construction (2) Pairwise comparison and priority vectors (3) Supermatrix formation and transformation (4) Final priorities.

Research Framework

The whole research procedures are as follows. First, patent data of interested technological area is collected. Second, technological cross-impact matrix is constructed with the confidence values calculated by applying ARM to the co-classification information of gathered patent data. Finally, core technologies are identified through employing ANP to the technological cross-impact matrix. Figure 1 depicts overall process of this study. Note that the rectangle denotes an individual process and the ellipse denotes the methodology for the next process. More detailed explanations are provided below.

Figure 1. Overall process of proposed approach



Technological cross-impact matrix construction

First of all, the technological area to be analyzed should be decided before constructing cross-impact matrix. For this aim, this research adopted patent classification system. Patent classification system stands for the hierarchical system to classify and manage patents considering their technological characteristics. Generally, patents are affiliated to more than two classes based on the patent classification system [42]. Class, therefore, indicates which technological areas the patents (individual technologies) are affiliated in technological classification systems.

The cross-impact index, *Impact(A,B)* is defined to the conditional probability, *P(B|A)*, which is of the same formula with the confidence of the association rule $A \rightarrow B$ in ARM. Accordingly, this study applies ARM to the co-classification information of gathered patents for constructing cross-impact matrix. Figure 2 expresses the cross-impact matrix with the confidence value between two technological areas. In this figure, T_i means the i^{th} technological area (class), and $conf(T_i \rightarrow T_j)$, the confidence values of the association rule $T_i \rightarrow T_j$, indicates the impact of the technological area of T_i on that of T_j. The values of the diagonal cells are 1 since the same technological areas impacts fully on each other.

Core technology identification

Previous studies on the analysis of technological cross-impact with patent classification information focus only to the identification of technology pairs with high cross-impact value. On the contrary, this study tries to grasping the most influential technologies based on the overall cross-impact that one technology impacts to all other technologies. To this aim, ANP, one of the MCDM methods, is applied to the redefined cross-impact matrix.

Figure 2. Technological cross-impact matrix

	T_1	T_2	…	T_n
T_1	1	$Conf(T_1 \rightarrow T_2)$		$Conf(T_1 \rightarrow T_n)$
T_2	$Conf(T_2 \rightarrow T_1)$	1		$Conf(T_2 \rightarrow T_n)$
…			1	…
T_n	$Conf(T_n \rightarrow T_1)$	$Conf(T_n \rightarrow T_2)$	…	1

Illustrative Example

Technology selection and patent data collection

The information and communication technology (ICT) industry has been at the forefront of industrial globalization [43]. ICTs can be classified into four categories: telecommunication, consumer electronics, computer and office machinery, and other ICT [44]. Among them, telecommunication technologies have been playing a critical role in economic growth and exhibiting dramatic technological progress [16]. Thus, analyzing the telecommunication technology is expected to provide valuable implication.

The primary source of patent data used in this study is the United States Patent and Trademark Office (USPTO) database. The USPTO has classified granted patents into corresponding technology classes defined by the USPC (United States Patent Classification). A class generally delineates one technology from another and serves as a unit of the analysis.

For selecting patents regarding telecommunication, the IPC (International Patent Classification) codes for ICT shown in Appendix are used. Referring to the US-to-IPC concordance provided by the USPTO website, the USPTO classes matched with the IPC codes of telecommunication technologies were chosen. The selected classes cover 13 classes in the USPC shown in Table 2.

Table2. Telecommunication technology classes

Class	Title
329	Demodulators
331	Oscillators
332	Modulators
340	Communications: electrical
341	Coded data generation or conversion
342	Communications: directive radio wave systems and devices (e.g., radar, radio navigation)
343	Communications: radio wave antennas
367	Communications, electrical: acoustic wave systems and devices
370	Multiplex communications
375	Pulse or digital communications
379	Telephonic communications
380	Cryptography
455	Telecommunications

Technological cross-impact matrix construction

To calculate cross-impact index and construct cross-impact matrix of telecommunication technologies, ARM is applied to the co-classification information of the patents assigned to the 13 classes registered in 2005. SAS E-miner release 4.3, one of data-mining package, is used and Apriori algorithm is selected to search rules. Ultimately, as shown in Table 3, the technological cross-impact matrix of telecommunication is constructed with the derived confidence values.

Core technology identification

The next step is to identify core technology by prioritizing technologies with employing ANP to the constructed technological cross-impact matrix. First, network model is constructed. The network in the proposed approach is made on the basis of cross-impact relationships represented in the cross-impact matrix. A cluster in the ANP network corresponds to a class and each cluster has no elements. In the ANP context, then, the resulting network model only includes alternative clusters, contrary to the general network model in the ANP comprised of a goal cluster, criteria clusters, and alternative clusters. Thus, the importance of alternatives (classes) is only evaluated with respective to impacts on other alternatives.

Second, the alternatives are pair-wisely compared and priority vectors are derived. The basic form of measurement in the ANP is a pairwise comparison with a scale of 1-9. However, pairwise comparisons do not have to be done in the proposed approach. It is implicitly assumed that the cross-impact index between two classes is a proxy of intensity of influence. Then, the importance of classes can be directly measured from the cross-impact matrix. Furthermore, since the alternatives have no elements, the cross-impact matrix itself is a priority vector and a supermatrix.

Third, supermatrix is constructed and transformed. As mentioned above, the supermatrix is the cross-impact matrix and need to be transformed into the weighted supermatrix and the

Table 3. Technological cross-impact matrix of telecommunication

Class	329	331	332	340	341	342	343	367	370	375	379	380	455
329	1.000	0.050	0.109	0.009	0.015	0.024	0.000	0.003	0.053	0.805	0.000	0.000	0.236
331	0.003	1.000	0.019	0.007	0.010	0.006	0.002	0.001	0.004	0.137	0.001	0.004	0.086
332	0.105	0.116	1.000	0.017	0.048	0.014	0.000	0.000	0.045	0.655	0.006	0.006	0.232
340	0.000	0.001	0.001	1.000	0.015	0.064	0.016	0.015	0.031	0.018	0.021	0.003	0.084
341	0.001	0.005	0.040	0.003	1.000	0.003	0.001	0.001	0.020	0.082	0.014	0.003	0.018
342	0.002	0.003	0.001	0.164	0.003	1.000	0.059	0.017	0.026	0.046	0.003	0.001	0.158
343	0.000	0.001	0.000	0.046	0.001	0.068	1.000	0.001	0.005	0.005	0.005	0.000	0.092
367	0.001	0.001	0.000	0.144	0.002	0.063	0.003	1.000	0.002	0.011	0.005	0.000	0.008
370	0.001	0.000	0.001	0.026	0.005	0.007	0.001	0.000	1.000	0.137	0.080	0.003	0.181
375	0.024	0.025	0.020	0.019	0.033	0.019	0.002	0.001	0.214	1.000	0.026	0.004	0.152
379	0.000	0.000	0.000	0.032	0.008	0.002	0.002	0.001	0.173	0.037	1.000	0.003	0.178
380	0.000	0.004	0.001	0.016	0.006	0.003	0.000	0.000	0.028	0.021	0.010	1.000	0.052
455	0.006	0.013	0.006	0.073	0.006	0.053	0.027	0.001	0.227	0.122	0.103	0.008	1.000

limit supermatrix.

The weighted supermatrix shown in Table 4 is constructed by manipulating the sum of columns elements of the supermatrix to be zero. Then, the limit supermatrix was derived by raising the weighted supermatrix to powers. Table 5 shows the limit supermatrix.

Finally, the priority is finalized and core technologies are identified. The columns of the limit supermatrix represent final priorities. This indicates importance of technologies in terms of impacts on other technologies, taking all the direct and indirect influences into consideration. The technology with the highest column value is 329 (Demodulators), and the next is 332 (Modulators). It is obvious that these technologies have significant impacts on other technologies, and therefore they are considered as the core technologies of the telecommunication technology network. The class whose column value is the lowest is 370 (Multiplex communications).

Table 4. Weighted supermatrix

Class	329	331	332	340	341	342	343	367	370	375	379	380	455
329	0.8763	0.0411	0.0911	0.0057	0.0128	0.0178	0.0000	0.0028	0.0290	0.2620	0.0000	0.0000	0.0953
331	0.0025	0.8210	0.0159	0.0042	0.0089	0.0042	0.0017	0.0005	0.0020	0.0445	0.0004	0.0036	0.0349
332	0.0916	0.0951	0.8351	0.0109	0.0417	0.0106	0.0000	0.0000	0.0247	0.2132	0.0044	0.0054	0.0935
340	0.0002	0.0009	0.0004	0.6430	0.0129	0.0480	0.0139	0.0144	0.0171	0.0057	0.0167	0.0028	0.0340
341	0.0010	0.0039	0.0335	0.0019	0.8684	0.0023	0.0008	0.0006	0.0107	0.0267	0.0108	0.0029	0.0071
342	0.0014	0.0021	0.0008	0.1051	0.0025	0.7548	0.0528	0.0163	0.0143	0.0148	0.0023	0.0012	0.0637
343	0.0000	0.0007	0.0000	0.0296	0.0008	0.0512	0.8992	0.0009	0.0028	0.0015	0.0035	0.0000	0.0373
367	0.0007	0.0007	0.0000	0.0925	0.0020	0.0477	0.0027	0.9617	0.0013	0.0035	0.0036	0.0000	0.0034
370	0.0009	0.0003	0.0008	0.0168	0.0043	0.0054	0.0011	0.0002	0.5470	0.0444	0.0627	0.0033	0.0732
375	0.0207	0.0208	0.0167	0.0122	0.0286	0.0145	0.0014	0.0012	0.1168	0.3253	0.0208	0.0040	0.0613
379	0.0000	0.0001	0.0002	0.0206	0.0067	0.0013	0.0021	0.0007	0.0949	0.0119	0.7862	0.0025	0.0720
380	0.0000	0.0030	0.0008	0.0105	0.0056	0.0020	0.0000	0.0000	0.0152	0.0070	0.0079	0.9668	0.0208
455	0.0048	0.0105	0.0048	0.0469	0.0049	0.0402	0.0243	0.0008	0.1241	0.0395	0.0807	0.0075	0.4036

Conclusions

This study suggests a systemic approach to identify core technology from the perspectives of the technological cross-impact. For this purpose, ARM is applied to the patent co-classification data and technological cross-impact matrix is constructed with the derived confidence value of each technology. Then, ANP, one of the MCDM methods, is employed to prioritize technologies. To illustrate the process of executing and utilizing the proposed approach, an example of telecommunication is presented.

The main contribution of this study is as follows. First, ARM is applied to the analysis of patents. ARM is one of the representative data mining techniques for exploring information of large database, but the study that applied it to the analysis of patents is hardly seen. In this study, ARM is employed to calculate the cross-impact index which has the same

Table 5. Limit supermatrix

Class	329	331	332	340	341	342	343	367	370	375	379	380	455
329	0.2972	0.2972	0.2972	0.2972	0.2972	0.2972	0.2972	0.2972	0.2972	0.2972	0.2972	0.2972	0.2972
331	0.0449	0.0449	0.0449	0.0449	0.0449	0.0449	0.0449	0.0449	0.0449	0.0449	0.0449	0.0449	0.0449
332	0.2632	0.2632	0.2632	0.2632	0.2632	0.2632	0.2632	0.2632	0.2632	0.2632	0.2632	0.2632	0.2632
340	0.0171	0.0171	0.0171	0.0171	0.0171	0.0171	0.0171	0.0171	0.0171	0.0171	0.0171	0.0171	0.0171
341	0.0820	0.0820	0.0820	0.0820	0.0820	0.0820	0.0820	0.0820	0.0820	0.0820	0.0820	0.0820	0.0820
342	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320	0.0320
343	0.0312	0.0312	0.0312	0.0312	0.0312	0.0312	0.0312	0.0312	0.0312	0.0312	0.0312	0.0312	0.0312
367	0.1001	0.1001	0.1001	0.1001	0.1001	0.1001	0.1001	0.1001	0.1001	0.1001	0.1001	0.1001	0.1001
370	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115
375	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263
379	0.0186	0.0186	0.0186	0.0186	0.0186	0.0186	0.0186	0.0186	0.0186	0.0186	0.0186	0.0186	0.0186
380	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577	0.0577
455	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182	0.0182

formula with the confidence. Second, this study applies the ANP to a technology network. The importance of technologies in terms of impacts on other technologies in the technology network could be measured with ANP. Finally, the suggested approach could help technology planners to formulate strategy and policy for technological innovation.

This study, however, is still subject to some limitations and these limitations are issues for further research. First, the proposed approach is illustrated with analyzing patents on the class level and so applying ANP is restricted to only clusters with no elements. Extending the analysis to the sub-class level of patents could make use of the full potential of ANP. Second, the cross-sectional analysis of the telecommunication patents registered in 2005 is conducted. A dynamic analysis on the telecommunication is expected to provide useful information on the change of technological trend. An extension of analysis to all technologies in ICT could be considered as future research issues. Finally, the selected 13 patent classes as telecommunication technologies are by no means exhaustive. A more systematic procedure is required to select the target classes.

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Appendix. ICT classification and corresponding IPC codes

ICT	IPC Code
Telecommunication	G01S, G08C, G09C, H01P, H01Q, H01S3/(025, 043, 063, 067, 085, 0933, 0941, 103, 133, 18, 19, 25), H1S5, H03B, H03C, H03D, H03H, H03M, H04B, H04J, H04K, H04L, H04M, H04Q
Consumer electronics	G11B, H03F, H03G, H03J, H04H, H04N, H04R, H04S
Computers /office machinery	B07C, B41J, B41K, G02F, G03G, G05F, G06, G07, G09G, G10L, G11C, H03K, H03L
Other ICT	G01B, G01C, G01D, G01F, G01G, G01H, G01J, G01K, G01L, G01M, G01N, G01P, G01R, G01V, G01W, G02B6, G05B, G08G, G09B, H01B11, H01J(11/, 13/, 15/, 17/, 19/, 21/, 23/, 25/, 27/, 29/, 31/, 33/, 40/, 41/, 43/, 45/), H01L

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