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Identifying Core Robot Technologies by Analyzing Patent Co-classification Information

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Abstract This study suggests a new approach for identifying core robot tech-nologies based on technological cross-impact. Specifically, the approach applies data mining techniques and multi-criteria decision-making methods to the co-classification information of registered patents on the robots. First, a cross-impact matrix is constructed with the confidence values by applying association rule mining (ARM) to the co-classification information of patents. Analytic network process (ANP) is applied to the co-classification frequency matrix for deriving weights of each robot technology. Then, a technique for order performance by similarity to ideal solution (TOPSIS) is employed to the derived cross-impact matrix and weights for identifying core robot technologies from the overall cross-impact perspective. It is expected that the proposed approach could help robot technology managers to formulate strategy and policy for technology planning of robot area.

Keywords Core robot technology, patent co-classification, cross-impact analysis, association rule mining, analytic network process

I. Introduction

Recently, interest in the 4th industrial revolution has increased (Jeon and Suh, 2017) and among various innovative technologies, interest in robots is increasing. In the 20th century, robots mainly served the role of automated equipment in factories in many industries (Choi et al., 2014; Park et al., 2009; Baeg et al., 2008; Lee et al., 2005). In the high-tech industry of the 21st century, however, robots are quickly evolving into an essential convenience for our civilization, be it at homes or in offices. The value of the robotics industry was calculated at approximately $8.4 billion in 2011 and has grown steadily since

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then. With the industry projected to grow at an annual rate of 12.5% over the 2010-2020 period, to be worth $30.3 billion in 2020, robot technology is clearly an area with high growth potential (Jung, 2008). Technologically advanced countries are taking note of this expansion trend in the robotics industry and are accordingly focusing their efforts on the development of various robot technologies (EUROP, 2009; Shin, 2012).

Unlike in the past, where industrial robots were its primary example, the robotics industry is now characterized by a gradual confluence of traditional industries and elements from nanotechnology (NT), biotechnology (BT) and information technology (IT) to cater to a new market according to consumer needs (Seo and Ahn, 2009). In order to possess and retain a competitive advantage in these circumstances, identifying the overall structure of robot technology and the relations among its components is very important. This refers to the activity of overseeing the trends in and the development of robot technology by identifying the sub-technologies of which robot technology is composed and the manner in which these sub-technologies affect one another. Through this activity, companies can efficiently and systematically manage their R&D portfolios, which leads to the assumption and maintenance of dominance in the competitive market (EIRMA, 2000).

The technological structure and relationship identification is mainly conducted with patent analysis (Trajtenberg et al., 1997). Not only is it the case that approximately 80% of all the technological knowledge (Blackman, 1995) is patented, patents are also convenient for accessing and analyzing technologies by researching various types of official and commercial databases. For these reasons, patents are recognized as providing useful information for technological analysis and R&D management (Yoon and Park, 2004) and many studies have tried to analyze technological relationships by analyzing patent information.

Among the components of patent information, citation information is most widely used to analyze technological relationships. The basic assumption of citation analysis is that because the knowledge of a cited patent flows into the citing patent, there exists a technological link between the two patents. Citation analysis has several advantages, such as usefulness, accessibility and convenience, but has certain attendant limitations. For example, since the average time-difference between citing and cited patents is more than 10 years (Hall et al., 2001), there is a fundamental limit in analyzing technological relationships according to the time difference. Furthermore, because only the citing-cited relationship between individual patents is taken into account, it is difficult to identify a more informative technological relationship between two patents as well as the characteristics in the technological field perspective (Yoon and Park, 2004).

Many proposals for the analysis of technological relationships among patents have been presented to address these limitations, such as co-citation (Lai and Wu, 2005; Stuart and Podoly, 1996), co-word (Courtial et al., 1993) and keyword vector (Yoon and Park, 2004). However, using co-citation information does not solve the problem of the large time difference between the citing and the cited patents. Furthermore, both co-word and keyword information relies on the researcher's intuition or judgment for a successful analysis, which makes it difficult to derive consistent results.

On the other hand, co-classification has several advantages. Co-classification analysis focuses on the technological relations between patents based on the fact that they are classified into some technological classes according to their technological characteristics (OECD, 1994). It assumes that the frequency with which two classification codes are jointly assigned to a patent document can be interpreted as the strength of the relationships between the two classification codes, in terms of knowledge relationships and spillovers (Breschi et al., 2003). Because co-classification analysis is different from citation analysis, since the former relies on the technological classification system, co-classification analysis can identify the relationship between technologies at various levels and not merely at an individual patent level. In other words, because the patent classification system generally has a hierarchical structure, technological levels can be differentiated in analysis depending on the purpose of a particular study. Moreover, errors from the time lag are not relatively significant because the time of a patent's classification information is identical to its registration time.

Among the methods utilizing patent co-classification information, technological cross-impact analysis (CIA) has been used to identify core technologies based on the interrelationships among them. The index for analyzing technological cross-impact is called the cross-impact index. However, calculating cross-impact index based on big patent data is only possible by developing a computer program for this. Moreover, a previous study analyzing technological cross-impact based on patent classification focuses only on identifying pairs of technologies with high cross-impact values (Choi et al., 2007) and does not consider the overall cross-impact of each technology on other technologies on the whole.

In response to the above issues and considerations, we propose a new method to identifying core robot technologies in terms of cross-impact based on patent co-classification information by taking into account the interrelationships among robot technologies. Our proposed approach is composed of three methods: an analytic network process (ANP), association rule mining (ARM) and the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS). We first use ARM, one of the representative data mining techniques for investigating vast databases, to calculate the technological cross-impact index. As a confidence in ARM has a form of a conditional probability, the formulas of the confidence and the cross-impact index are the same. So we adopt it to evaluate the cross-impact of robot technology. Following this, we employ TOPSIS, a multi-criteria decision making method (MCDM), to investigate core robot technology with regard to its impact on robot technologies on the whole. ANP is applied in order to derive the weight of each criterion for the performance of TOPSIS.

The remainder of this study is organized as follows. In Section 2, we review the literature related to patent analysis and introduce the background of ARM, ANP and TOPSIS. We present our proposed approach in Section 3 and provide an instance of its implementation with a case study in Section 4. In Section 5, we conclude and highlight directions for future research.

II. Literature Review

1. Patent Analysis

A patent is the primary result of an R&D activity and describes the source and characteristics of a new technology. Not only are patents acknowledged as a vast and useful data source for technology management-related research, they are also utilized as a representative proxy for technological analysis (Grilliches, 1990). Patents have limits like all other technological data (Ernst, 2003; Archibugi and Pianta, 1996; Grilliches, 1990) and there are endless disputes over the use of patents in technological analysis. However, as patents facilitate quantitative analysis, they are more advantageous than data used for conceptual or qualitative analysis. Moreover, patent databases include data on activities in most areas of technological innovation. On account of these reasons, patents are widely used as data for technological analysis.

The initial method used for patent analysis is a simple comparison among the number of patents applied for by different individuals or entities, such as countries, companies or fields of technology (Wartburg et al., 2005). In other words, the greater the number of patent applications by an individual, the greater the importance of that individual. However, there are many cases where patent distribution is very asymmetric. Thus, evaluating the importance of an individual based simply on the number of patent applications leads to biased results in most cases (Harhoff et al., 1999). Moreover, there is a limit in the observation of the relationship between individual patents.

Methods that solve the above-mentioned problems are patent citation analysis and patent classification analysis. First, patent citation analysis uses the citation relationship between two patents based on the assumption that there is a technological connection between them because the knowledge of a cited patent flows to a citing patent (Narin, 1994). Patent citation analysis can be largely distinguished into two classes according to its purpose. The first is a determination of the value of the patent and is based on the number of cited patents. Patents that have been cited more than others are determined to have a higher technological and economic importance (Breitzman and Thomas, 2002; Narin et al., 1987; Trajtenberg, 1990). Many studies use citation number as the index for measuring patent quality (Reitzig, 2004; Ernst, 2003; Lanjouw and Schankerman, 1999; Hirschey and Richardson, 2001). The second class of patent citation analysis is the relationship search between technologies, whereby patent citation is used to identify the knowledge transfer of technologies, or their technological linkage. Studies related to this include technological overlap analysis between cooperative companies (Mowery et al., 1998), proposals for new patent classification systems through patent clustering (Lai and Wu, 2005) and core technology identification through technology network construction (Lee et al., 2009).

In contrast, patent classification analysis is based upon a hierarchical system of patent classification information in order to categorize patents with complex technology information into groups that are easy to understand. All patents are classified into one or more categories. Research has shown that classification is the most appropriate analysis unit to search for knowledge in a patent (Dibiaggio and Nesta, 2005). A patent referee determines the classification of patents and a patent is typically part of several categories. There are two primary purposes of patent classification analysis. The first is the measurement of relatedness between technologies and is based on the assumption that when a patent is affiliated with two or more classes, the technologies in each class are related to those in the other. Hence, measurement relatedness specifies that the higher the number of such patents, the stronger the relationship or similarity between the relevant technological fields. The representative index for measuring the relatedness between technologies is the cosine index. Cosine index is a form of correlation coefficient and evaluates the relatedness between two technologies based on a correlation with all other technologies. If the distribution of two technologies is the same, the value of the cosine index is 1. The value is 0 when there is no coincidence. The representative studies that use cosine index are studies by Jaffe (Jaffe, 1986; Jaffe, 1989), who used patents belonging to companies in the United States to observe the distribution in 49 technologies and to measure the relatedness between them. There are various other studies using cosine index, such as the structure identification of science and technology (Tijssen, 1992), the analysis of technological knowledge diffusion (Grupp, 1996) and the analysis of the relationship between technological distance and technology diversification (Breschi et al., 1998).

The second major purpose of patent classification analysis is technological cross-impact analysis. Technological change and progress can occur through various events or incidents and cross-impact is the effect of one such incident on another. Patents are classified according to function, use, or structure. The impact relationship between technologies is identified by these characteristics. The cross-impact index of a technology A and B - *Impact(A, B)* - is defined as a conditional probability: $P(B|A)=N(A\cap B)/N(A)$ (Kim et al., 2011). Here, $N(A)$ refers to the total number of patents affiliated to technology A and $N(A\cap B)$ is the number of patents affiliated to both technology A and B. The cross-impact index has a value between 0 and 1: if the value is near to 1, the impact of technology A on technology B is significant.

2. Association Rule Mining (ARM)

ARM is a data mining technique used to find interesting and useful association rules between items in a huge database. An association rule is a phenomenon whereby the generation of an item in a transaction leads to the simultaneous generation of another item. From a conceptual point of view, there is a strong association between simultaneously generated items (Han and Kamber, 2001). ARM is widely used in various fields, especially in marketing (Liao and Chen, 2004), bioinformatics (Creighton and Hahash, 2003), healthcare (Ca and Jiang, 2003) and finance (Hsieh, 2004).

In ARM, the three evaluation criteria for the usefulness of association rules are support, confidence and lift, as specified in Table 1. Among the measures in Table 1, the meaning of lift is as follows. If the numeric value is greater than 1, the possibility of the simultaneous occurrence of two items X and Y is higher than that of the separate occurrence of X and Y, and there is a positive relatedness between the two. If the numeric value is 1, the probability of both a simultaneous and a separate occurrence is the same and the two items are considered independent of each other. If the numeric value is less than 1, the probability of simultaneous occurrence is higher than the possibility of separate occurrence and there is a negative relatedness between the two items.

Table 1 Measures for the interestedness of association rules

Measure	Description	Formula
Support	In the association rule X→Y, the possibility of simultaneous occurrence of X and Y item	$P(X\cap Y)$
Confidence	In the association rule X→Y, possibility of transaction including X to also include Y	$P(Y\mid X)$
Lift	In the association rule X→Y, statistical dependence of X and Y	$\frac{P(Y\mid X)}{P(Y)}$

ARM generally progresses at the following two levels (Agrawal and Srikant, 1984): (1) frequent itemset search: producing a combination of all items with over the minsupport value and (2) association rule creation: in the frequent itemset, selecting rules for minconfidence or standard lift. Of these levels (1) is time-consuming and its representative method is an a priori algorithm.

3. Analytic Network Process (ANP)

ANP is a generalization of the analytic hierarchy process (AHP), which is one of the most widely used MCDM methods (Saaty, 1996). AHP breaks down a problem into several levels of a hierarchical structure and assumes that each decision-making element is independent of the others. ANP is an expansion of AHP for a problem with dependencies and feedback. In other words, ANP converts the hierarchical structure of AHP into a network to facilitate application even in instances of complex correlations between decision elements (Meade and Sarki, 1999). ANP has recently been applied to patent data for technology selection (Shen et al., 2011), core technology identification (Lee et al., 2009; Kim et al., 2011), R&D project evaluation (Jung and Seo, 2010) and R&D partner selection (Geum et al., 2013).

ANP is generally conducted in four steps (Lee et al., 2009). First, the network model is constructed to structure the given problem into a network form. The network node is a cluster and the decision-making elements of each cluster can affect the elements of other clusters. Arrows depict this relationship. If there is a relationship between decision elements of the same cluster, a feedback loop is used to signify this. Second, pairwise comparison is used to derive a priority vector. The element of each cluster performs pairwise comparison not only on the side of impact to another element, but also on the interdependency perspective. If a cluster-weighted value is required in order to create the next level of supermatrix, a pairwise comparison is carried out between the clusters. Further, the eigenvector method is applied to each pairwise comparison matrix to derive the partial priority vector it. Third, the supermatrix is constructed and converted. It collects all partial priority vectors (submatrix) to form a single large matrix. The supermatrix is thus divided into submatrix regions, where each submatrix shows the relationship between two clusters. If there is no relationship among the clusters, the relevant region is a zero matrix. Given all submatrices, the weighted supermatrix is calculated by multiplying weight values of the relevant clusters and normalizing for the sum of column in the large matrix to be 1. When the sum of the values of all columns in the matrix is 1, multiplying this weighted supermatrix infinitely is known to collect the only form (Datta et al., 2014). Therefore, the "column stochastic" characteristic of the weighted supermatrix becomes a precondition for the construction of the limit supermatrix.

Moreover, infinite power is performed until the weighted supermatrix is collected to derive the limit supermatrix. Finally, the final priority vector is derived. The final priority of the alternatives can be obtained by the column vector value in the limit supermatrix and this reflects all direct and indirect impact of each element on other each elements.

4. Technique for Order Performance by Similarity to Ideal Solution (TOPSIS)

TOPSIS is same as other MCDM methods in that it handles decision problems in situations where many criteria and alternatives exist. TOPSIS was first proposed by Hwang and Yoon (Hwang and Yoon, 1981). Its greatest advantage over other MCDM methods is that the only subjective element required in evaluation of alternatives is the weights of the relevant criteria and the focus is on evaluating the alternative and not on generating the weights (Olson, 2004). It also has the following characteristics (Kim et al., 1997). First, the logic of the decision-making of TOPSIS is similar to the principle of human selection. When there is an ideal alternative, everyone tries to select it. However, due to realistic limits, the most useful viable alternative is selected instead. Second, TOPSIS provides a scalar quantity that takes into account both the positive and negative ideal alternative. Third, TOPSIS involves simple calculation that can be easily programmed through spreadsheets. It is used in various fields, such as manufacturing policy evaluation (Cha and Jung, 2003), web resource evaluation (Zhu and Buchman, 2002), product design (Lin et al., 2008) and service quality evaluation (Tsaur et al., 2002; Mukherjee and Nath, 2005).

The TOPSIS procedure is as follows (Hwang and Yoon, 1981):

Step 1. All components of the decision matrix consist of alternatives and criteria. In other words, the performance scores are normalized as follows:

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{M} x_{ij}^2}} \quad (1)$$

where M refers to the number of alternatives and is the performance score on the jth criterion of the i^{th} alternative.

Step 2. The following criteria of weighted value are multiplied with the prior normalized decision matrix for calculating the weighted formal decision matrix:

$$WY = \omega_i y_{ij} \quad (2)$$

where is the weighted value of the j^{th} criterion.

Step 3. The positive ideal solution (S^+) and the negative ideal solution (S^-) are calculated (Santhanam et al., 2015).

$$S^+ = \max(\omega_i y_{ij}), S^- = \min(\omega_i y_{ij})$$
$$i = 1, 2, ..., M \tag{3}$$

Step 4. The Euclidean distance between each alternative and the positive ideal solution is calculated and the Euclidean distance between each alternative and the negative ideal solution is calculated as follows:

$$D_i^+ = \sqrt{\sum_{i=1}^{N} (S_j^+ - \omega_i y_{ij})^2}, \quad i = 1, 2, ..., M \tag{4}$$

$$D_i^- = \sqrt{\sum_{i=1}^{N} (\omega_i y_{ij} - S_j^-)^2}, \quad i = 1, 2, ..., M \tag{5}$$

where N is the number of criteria.

Step 5. The similarity between each alternatives and the positive ideal solution is calculated. The similarity between the i^{th} alternative and the positive ideal alternative is defined as follows (Fu et al., 2010):

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-}, 0 \le C_i \le 1, i = 1, 2, ..., M \tag{6}$$

Step 6. The order of the alternatives is determined on the basis of the similarity of each alternative to the positive ideal solution, which is calculated in Step 5. The alternative with a higher similarity value has a higher priority.

III. Research Framework

The process of identifying core robot technology using patent co-classification information is as follows. First, the patent data for robot technology is collected. Second, the cross-impact matrix is built with the confidence values derived by applying ARM to the co-classification information of the patent data gathered. Third, the weight of each robot technology is derived by carrying out an ANP on the co-occurrence matrix created using co-classification frequency information. Finally, using the derived weights of robot technologies, TOPSIS is performed on the cross-impact matrix to identify the core robot technology. Fig. 1 shows the flow of the overall process in this study. The details of the each process are described below.

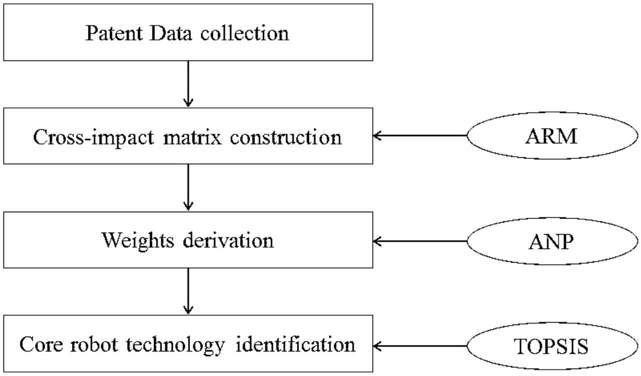

Figure 1 Research process

1. Patent Data Collection

The identification of the affiliation of the relevant robot technology in the patent classification system is required prior to collecting patent data. The patent classification system is a hierarchical system for classifying and managing patents with the consideration of their technological characteristics. The technological characteristics of a patent are identified with the patent claim, which lists the new features of patents. Because patents generally have two or more technological characteristics, they are mostly affiliated with several classes in the patent classification system.

2. Cross-Impact Matrix Construction

A cross-impact matrix is constructed to identify the core robot technology from a cross-impact perspective. The matrix is created by allocating cross-impact index values among all robot technologies calculated by using the co-classification information of the relevant patent on the matrix cell (Kim, 2016). However, a separate program must be used to calculate cross-impact index from a large database, such as the patent database. Therefore, we use ARM to derive the cross-impact index. Patent classification analysis is similar in its concept to a market basket analysis using ARM as follows (Kim et al., 2011). A patent referee’s activity to decide the classification of any patent stands for selecting the most representative technologies which that patent wishes to describe among various technologies, therefore it is much like a customer’s activity to buy the most necessary goods among various things. Moreover, patent classification information recorded by a patent referee is relevant to the sets of goods purchased by the customer. Therefore, the patent, classification action, classification and the classification information of individual patents in patent classification analysis correspond to the identifier, transaction, item and the itemset, respectively, in ARM.

As described in Section 2.1, the cross-impact index of technology A and B, *Impact(A, B)*, can be defined as a conditional probability P(B|A). Because the confidence of the association rule $A \rightarrow B$ in ARM is also defined as P(B|A) , we apply ARM to the co-classification information of the gathered patents for constructing cross-impact matrix. Table 2 shows the form of the cross-impact matrix. Here, T_i indicates the technology from field i and Conf ($A \rightarrow B$) refers to the confidence value of the association rule $A \rightarrow B$ (Seo et al., 2016). In other words, the value of each cell of the cross-impact matrix is the impact of the technology in the relevant row on the technology listed in the relevant column. The diagonal values of the matrix are set to 1 because there is a 100% cross-impact relationship between technologies in the same field.

Table 2 A form of cross-impact matrix

Technology \ Technology	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

3. Weight Derivation

Performing TOPSIS requires the weight information for the evaluation criteria. For this, we apply ANP to the patent co-classification frequency information between the robot technologies. After composing the co-classification frequency matrix, both the rows and column of which represent technologies, ANP is applied by considering the direct and indirect relationships among all robot technologies to derive the technology weights.

The first two steps of ANP - network model construction and pairwise comparison & local priority vectors - are not required in our proposed approach (Kim, 2012). A network model in ANP is constructed based on expert judgment in order to model an abstract decision problem. However, the network in the proposed approach is designed on the basis of technological relationships represented in the co-classification frequency matrices (Lee et al., 2009). A cluster in the ANP network corresponds to an upper level classification and elements in one cluster are equivalent to lower lever classifications within an upper level classification. Then, in the ANP context, the resulting network model only includes alternative clusters, contrary to the general network model in the ANP that comprises a goal cluster, criteria clusters and alternative clusters.

Therefore, the importance of alternatives is only evaluated with respect to their effects or influences on other alternatives, not with respect to some criterion or goal. It implicitly assumes that the co-classification frequency between a pair of nodes is a proxy for the degree of influence between them. Thus, pairwise comparisons are not required and priority vectors can be directly obtained from the co-classification frequency matrix.

The supermatrix in ANP is a partitioned matrix consisting in all local priority vectors. The co-classification frequency matrix is equivalent to the supermatrix because the co-classification frequency matrix is a set of all local priority vectors. The weighted supermatrix, each of whose columns sums to one, is constructed by transforming the supermatrix. Then the limit supermatrix is derived by converging all the columns of the weighted supermatrix the same. This is called limit priorities and captures all the direct and indirect effects among robot technologies. The weights of each technology can then be determined based on the limit priorities of robot technologies.

4. Core Robot Technology Identification

The core robot technology is identified by employing TOPSIS. For this, the technology located on the row and the column of the cross-impact matrix indicated in Section III.2 is redefined in the alternative and criteria of decision-making problem. The weights between robot technologies found in the previous step are used for TOPSIS. Through these processes, the overall cross-impact relationship among robot technologies the value of each is reflected in the evaluation of technological importance. Table 3 is a conceptual schematization of the difference in core robot technology derivation before (a) and after (b) the application of the MCDM method.

As seen in Table 3(a), before applying the MCDM method, the quantitative cross-impact between robot technologies is used to calculate their technological importance. For example, the importance of technology T1 is calculated by the sum $\sum R_{1i}$ of its cross-impacts (R11, R12,···, R1n) on other technologies (T1, T2,···, Tn). As shown in Table 3(b), from the MCDM perspective, the weight of technology W_i is reflected for evaluation (Lee et al., 2017). Therefore, the importance of technology T1 is $\sum W_i R_{1i}$. By analyzing the overall relationship among many technologies in this way, each technology can be regarded as both an alternative and a criterion, due to which the MCDM method can be applied. There are advantages of reflecting simple quantitative relationships as well as the values of individual technologies in identifying technological cross-impact.

Table 3 Core robot technology identification through MCDM method

Technology \ Technology	T1	T2	…	Tn	Technological importance
T1	R11	R12		R1n	$\sum_{i=1}^{n} R_{1i}$
T2	R21	R22		R2n	$\sum_{i=1}^{n} R_{2i}$
…					…
Tn	R31	R32		Rnn	$\sum_{i=1}^{n} R_{ni}$

(a) Before MCDM introduction

Alternative \ Standard	T_1 (W_1)	T_2 (W_2)	…	T_n (W_n)	Technological importance
T_1	R_{11}	R_{12}		R_{1n}	$\sum W_i R_{1i}$
T_2	R_{21}	R_{22}		R_{2n}	$\sum W_i R_{2i}$
…					…
T_n	R_{31}	R_{32}		R_{nn}	$\sum W_i R_{ni}$

(b) After MCDM introduction

IV. Case Study

1. Patent Data Collection

Patents registered in the United States Patents and Trademark Office (USPTO) were selected as the data source for our case study. All patents registered with the USPTO are classified by the United States Patent Classification (USPC). Each USPC classification consists of a class and a subclass (USPTO, 2006). A class identifies a technology in relation to other technologies and a subclass categorizes sub-technologies within a class according to their structure and function. In the USPC, robot technology is in Class 901. As shown in Table 4, Class 901 is composed of 10 subclasses of indent level 0. We used these subclasses as our analysis unit. Of the patents affiliated with Class 901, we selected as our analysis subjects those applied for until 2012. Using a Java-based web document collection/parsing/database input program that we developed, we collected patents related to robot technology from the USPTO website and stored them in the database.

Table 4 Classification of robot technology

Indent Level 0	Indent Level 1	Indent Level 2	Indent Level 3
MOBILE ROBOT (1)			
arm MOTION CONTROLLER (2)	Teaching system	Manual lead through	
		Machine driven lead through	
	Communication with another machine	Conveyor	
		Robot	
	Closed loop (sensor feedback controls arm movement)	Sensor physically contacts and follows work contour	
	Mechanically actuated present limit	Cam	
		Limit switch	
arm MOVEMENT (SPATIAL) (14)	Jointed arm		
	Cartesian (X-Y-Z arm)		
	Cylindrical		
	Spherical		
DRIVE SYSTEM FOR arm (19)	With provision for altering speed of driven element		
	Flaccid drive element		
	Fluid motor		
	Electric motor	Stepper motor	
	Gearing	Including bevel gear	
arm PART (27)	Joint	Wrist	
END EFFECTOR (30)	Gripping jaw	Servo-actuated	Tactile sensor
			Force feedback
			Proximity
		Actuating means	Fluid motor
			Electric motor
		Jaw structure	
	Vacuum or magnetic		
	Tool	Welding	
		Spray painting or coating	
	Inspection		
	Compliance		
SENSING DEVICE (46)	Optical		
COUNTER BALANCE (48)			
PROTECTIVE DEVICE (49)			
MISCELLANEOUS (50)			

2. Cross-Impact Matrix Construction

To construct a cross-impact matrix for robot technologies, we carried out ARM on the co-classification information of patents classified to the 10 subclasses. We used the data-mining package SAS E-miner 9.3 and selected an a priori algorithm to search for rules. Cross-impact index for each technology pair is identified with the derived confidence values. Table 5 shows the 10 robot technology pairs in decreasing order of cross-impact values. Technology A influences technology B and *Impact(A, B)* is the cross-impact index of technology A on technology B. Also, the value of technology A and technology B indicated on each order in Table 5 is the subclass in which they are affiliated into.

The technology pair of technology 19 (DRIVE SYSTEM FOR arm) in Table 5 effects technology 14 (arm MOVEMENT (SPATIAL)) with a cross-impact value of 0.3590, which is the highest cross-impact. This means that among the patents included in technology 19, 35.9% are also classified in technology 14. Technology 19 is related to mechanical driving components of robotic arm joints. Technology 14 refers to trajectory (motion) generation of robot arm joints by moving in various coordinate systems. These technologies are related to driving mechanism design and motion generation, which have a high degree of mutual relatedness.

Table 5 Robot technology pairs with high cross-impact

Rank	Technology *A*	Technology *B*	*Impact(A,B)*
1	19	14	0.3590
2	27	19	0.3436
3	14	19	0.3214
4	46	30	0.3104
5	14	2	0.2946
6	46	2	0.2663
7	2	30	0.2628
8	48	14	0.2584
9	14	30	0.2516
10	48	19	0.2472

The pair of technology 27 (arm PART) effecting technology 19 has the next highest cross-impact value. Technology 27 is related to components of robot joint design. The joints are divided into shoulder, elbow and wrist and involve a combination of driving technologies, such as motor, reducer, controller and link.

The cross-impact matrix of the robot technology, created using the cross-impact index of all robot technology pairs, is in Table 6.

Table 6 Cross-impact matrix of robot technology

Technology	1	2	14	19	27	30	46	48	49	50
1	1.0000	0.2390	0.0906	0.0464	0.0532	0.1042	0.2106	0.0215	0.0340	0.0453
2	0.1362	1.0000	0.2343	0.1427	0.0704	0.2628	0.1872	0.0181	0.0284	0.0232
14	0.0649	0.2946	1.0000	0.3214	0.1502	0.2516	0.0804	0.0373	0.0422	0.0170
19	0.0372	0.2004	0.3590	1.0000	0.2421	0.1831	0.0390	0.0399	0.0209	0.0218
27	0.0605	0.1403	0.2381	0.3436	1.0000	0.2227	0.0541	0.0309	0.0386	0.0283
30	0.0376	0.1665	0.1268	0.0827	0.0708	1.0000	0.1383	0.0119	0.0217	0.0123
46	0.1708	0.2663	0.0909	0.0395	0.0386	0.3104	1.0000	0.0193	0.0202	0.0239
48	0.1067	0.1573	0.2584	0.2472	0.1348	0.1629	0.1180	1.0000	0.0337	0.0393
49	0.1230	0.1803	0.2131	0.0943	0.1230	0.2172	0.0902	0.0246	1.0000	0.0533
50	0.2105	0.1895	0.1105	0.1263	0.1158	0.1579	0.1368	0.0368	0.0684	1.0000

3. Weights Derivation

For deriving the weights of the evaluation criteria for operating TOPSIS, the co-classification frequency matrix was constructed as shown in Table 7. As explained in Section III.3, the co-classification frequency matrix is the supermatrix. The weighted supermatrix (Table 8) was derived by normalizing supermatrix, whose column sums are one. The limit supermatrix (Table 9) was constructed by converging the columns of the weighted supermatrix the same. The columns of the limit supermatrix represent the weight of each robot technology, considering all the direct and indirect relationships.

Table 7 Co-classification frequency matrix

Technology	1	2	14	19	27	30	46	48	49	50
1	0	211	80	41	47	92	186	19	30	40
2	211	0	363	221	109	407	290	28	44	36
14	80	363	0	396	185	310	99	46	52	21
19	41	221	396	0	267	202	43	44	23	24
27	47	109	185	267	0	173	42	24	30	22
30	92	407	310	202	173	0	338	29	53	30
46	186	290	99	43	42	338	0	21	22	26
48	19	28	46	44	24	29	21	0	6	7
49	30	44	52	23	30	53	22	6	0	13
50	40	36	21	24	22	30	26	7	13	0

Table 8 Weighted supermatrix

Technology	1	2	14	19	27	30	46	48	49	50
1	0.0000	0.1234	0.0514	0.0324	0.0524	0.0562	0.1743	0.0843	0.1101	0.1839
2	0.2831	0.0000	0.2341	0.1754	0.1216	0.2492	0.2721	0.1264	0.1606	0.1638
14	0.1070	0.2123	0.0000	0.3139	0.2055	0.1896	0.0931	0.2051	0.1904	0.0948
19	0.0548	0.1293	0.2552	0.0000	0.2970	0.1238	0.0400	0.1966	0.0849	0.1092
27	0.0632	0.0639	0.1191	0.2118	0.0000	0.1058	0.0395	0.1067	0.1101	0.1006
30	0.1230	0.2381	0.1997	0.1604	0.1922	0.0000	0.3168	0.1292	0.1927	0.1379
46	0.2494	0.1697	0.0640	0.0339	0.0468	0.2069	0.0000	0.0927	0.0803	0.1178
48	0.0253	0.0165	0.0296	0.0349	0.0266	0.0177	0.0194	0.0000	0.0229	0.0316
49	0.0404	0.0257	0.0336	0.0184	0.0335	0.0323	0.0206	0.0281	0.0000	0.0603
50	0.0539	0.0209	0.0134	0.0189	0.0245	0.0185	0.0241	0.0309	0.0482	0.0000

Table 9 Limit supermatrix

Technology	1	2	14	19	27	30	46	48	49	50
1	0.0778	0.0778	0.0778	0.0778	0.0778	0.0778	0.0778	0.0778	0.0778	0.0778
2	0.1784	0.1784	0.1784	0.1784	0.1784	0.1784	0.1784	0.1784	0.1784	0.1784
14	0.1619	0.1619	0.1619	0.1619	0.1619	0.1619	0.1619	0.1619	0.1619	0.1619
19	0.1316	0.1316	0.1316	0.1316	0.1316	0.1316	0.1316	0.1316	0.1316	0.1316
27	0.0938	0.0938	0.0938	0.0938	0.0938	0.0938	0.0938	0.0938	0.0938	0.0938
30	0.1704	0.1704	0.1704	0.1704	0.1704	0.1704	0.1704	0.1704	0.1704	0.1704
46	0.1113	0.1113	0.1113	0.1113	0.1113	0.1113	0.1113	0.1113	0.1113	0.1113
48	0.0233	0.0233	0.0233	0.0233	0.0233	0.0233	0.0233	0.0233	0.0233	0.0233
49	0.0286	0.0286	0.0286	0.0286	0.0286	0.0286	0.0286	0.0286	0.0286	0.0286
50	0.0228	0.0228	0.0228	0.0228	0.0228	0.0228	0.0228	0.0228	0.0228	0.0228

4. Core Robot Technology Identification

To investigate the core robot technology, TOPSIS was carried out on the cross-impact matrix derived in Section 4.2. Table 10 shows the weighted normalized matrix reflecting the weights of each robot technology derived in Section 4.3 on all elemental values of the cross-impact matrix.

The TOPSIS procedure calculates the positive ideal technology (S^+), the negative ideal technology (S^-), the distance between each technology and the positive ideal technology (D_i^+), the distance between each technology and the negative ideal technology (D_i^-) and the similarity between each technology and the positive ideal technology (C_i). Table 11 shows the overall result.

Table 10 Weighted normalized matrix

Technology	1	2	14	19	27	30	46	48	49	50
1	0.0745	0.0351	0.0121	0.0052	0.0047	0.0145	0.0217	0.0006	0.0011	0.0012
2	0.0101	0.1470	0.0313	0.0160	0.0062	0.0366	0.0193	0.0005	0.0009	0.0006
14	0.0048	0.0433	0.1337	0.0360	0.0132	0.0351	0.0083	0.0010	0.0014	0.0005
19	0.0028	0.0295	0.0480	0.1121	0.0213	0.0255	0.0040	0.0011	0.0007	0.0006
27	0.0045	0.0206	0.0318	0.0385	0.0881	0.0310	0.0056	0.0009	0.0013	0.0008
30	0.0028	0.0245	0.0170	0.0093	0.0062	0.1393	0.0143	0.0003	0.0007	0.0003
46	0.0127	0.0391	0.0122	0.0044	0.0034	0.0432	0.1031	0.0005	0.0007	0.0007
48	0.0080	0.0231	0.0345	0.0277	0.0119	0.0227	0.0122	0.0280	0.0011	0.0011
49	0.0092	0.0265	0.0285	0.0106	0.0108	0.0303	0.0093	0.0007	0.0328	0.0015
50	0.0157	0.0279	0.0148	0.0142	0.0102	0.0220	0.0141	0.0010	0.0022	0.0274

As shown in Table 11, technology 14 (arm MOVEMENT) resulted in the most important technology with respect to cross-impact between technologies. Technologies 2 (arm MOTION CONTROLLER), 30 (END EFFECTOR) and 19 (DRIVE SYSTEM FOR arm) are also important in that order. It is clear that these technologies have weighty effects on other technologies and are considered core robot technologies. The least important technologies are 50 (MISCELLANEOUS), 49 (PROTECTIVE DEVICE) and 48 (COUNTER BALANCE) in that order. This result is acceptable because technologies 2 and 19 are component technologies for designing robot joints and the connection of joints with links forms a robot arm and an end effector. We can thus conclude that technology 14 is directly related to technologies 2 and 19. Technologies 48 and 49 are secondary technologies for enhancing the performance or the dexterity of a robotic arm.

Table 11 TOPSIS result for robot technology

Technology	S^+	S^-	D_i^+	D_i^-	C_i	Rank
1	0.0745	0.0028	0.2652	0.0753	0.2212	7
2	0.1470	0.0206	0.2250	0.1313	0.3686	2
14	0.1337	0.0121	0.2220	0.1298	0.3688	1
19	0.1121	0.0044	0.2367	0.1157	0.3284	4
27	0.0881	0.0034	0.2456	0.0949	0.2787	6
30	0.1393	0.0145	0.2479	0.1255	0.3361	3
46	0.1031	0.0040	0.2464	0.1053	0.2994	5
48	0.0280	0.0003	0.2571	0.0452	0.1496	8
49	0.0328	0.0007	0.2612	0.0418	0.1379	9
50	0.0274	0.0003	0.2661	0.0355	0.1178	10

The results of this analysis can be used in corporate or national strategies for robot technology development. For example, in order to attain technological superiority in the robot industry, technologies related to arm MOVEMENT (SPATIAL) must be reinforced as a priority. This is because, if competitive superiority is achieved in this technology, the technological capability of other robot technologies can be easily reinforced. Furthermore, since the growth and development of one technology affect those of others, it can be used to predict technological progress. For example, technologies such as arm MOVEMENT (SPATIAL) or arm MOTION CONTROLLER have a weighty impact on the development of robot technology on the whole. Thus, the rapid development of these technologies is expected to lead to progress in overall robot technology.

V. Conclusion

We proposed a systematic approach for identifying core robot technologies from a cross-impact perspective. We applied ARM to a situation where a patent was part of two robot technology subclasses and used the resulting confidence values to construct a cross-impact matrix. For weighting, we applied ANP to the co-classification frequency matrix and used the derived limit priority value. We, then, used TOPSIS to identify the core robot technology from the perspective of its impact on robot technologies on the whole. In the application of TOPSIS, we redefined the rows and columns of the cross-impact matrix as the alternatives and the criteria of a decision-making problem, respectively. To verify the validity and the usefulness of the suggested approach, we conducted a case study of the USPTO database.

The contributions of this paper are as follows. First, we proposed a systematic method to identify core robot technologies. Second, we introduced ARM for patent analysis. ARM is a representative data mining technique for information search in large databases. There is an advantage to not requiring the implementation of a separate program for patent analysis, as the cross-impact index can be derived through a commercial package for ARM. Third, for the identification of core robot technology, we used ANP and TOPSIS, an MCDM method. Not only can cross-impact on overall robot technologies be considered through these, they can also reflect individual values of robot technologies. Finally, our proposed approach can provide useful information to formulate a technological strategy or policy for robot technology innovation. In particular, it can be utilized to identify the robot technology that ought to be prioritized to increase the competitiveness of a corporation in robot technology and can thus predict the progress of the field of robot technology.

Notwithstanding these contributions, this study has several limitations and calls for future research. First, the data collection period is limited to 2012.

Actually, our research had plan to identifying core robot technologies before the 4th industrial revolution and then identifying core robot technologies after the 4th industrial revolution. By comparing the core technologies before and after the 4th Industrial Revolution, the dynamic changes of robot can be analyzed. This is our future research topic. Second, from the perspective of technology classification, USPC is used. However, technology classification is changing according to the technological development. Therefore, instead of “static” classification such as USPC, “flexible” classification, which can be obtained by text mining or data mining of patent documents, can be applied as a new classification. Third, patent data is very useful in analyzing core technologies, but it does not include all the technologies. In future research, it is necessary to analyze additional academic papers or technical reports.

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