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Methodology of technological evolution for three-dimensional printing

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Abstract

Purpose – An increasing amount of attention is being paid to three-dimensional (3D) printing technology. The technology itself is based on diverse technologies such as laser beams and materials. Hence, 3D printing technology is a converging technology that produces 3D objects using a 3D printer. To become technologically competitive, many companies and nations are developing technologies for 3D printing. So to know its technological evolution is meaningful for developing 3D printing in the future. The paper aims to discuss these issues.

Design/methodology/approach – To get technological competitiveness of 3D printing, the authors should know the most important and essential technology for 3D printing. An understanding of the technological evolution of 3D printing is needed to forecast its future technologies and build the R&D planning needed for 3D printing. In this paper, the authors propose a methodology to analyze the technological evolution of 3D printing. The authors analyze entire patent documents related to 3D printing to construct a technological evolution model. The authors use the statistical methods such as time series regression, association analysis based on graph theory, and principal component analysis for patent analysis of 3D printing technology.

Findings – Using the proposed methodology, the authors show the technological analysis results of 3D printing and predict its future aspects. Though many and diverse technologies are developed and involved in 3D printing, the authors know only a few technologies take lead the technological evolution of 3D printing. In this paper, the authors find this evolution of technology management for 3D printing.

Practical implications – If not all, most people would agree that 3D printing technology is one of the leading technologies to improve the quality of life. So, many companies have developed a number of technologies if they were related to 3D printing. But, most of them have not been considered practical. These were not effective research and development for 3D printing technology. In the study, the authors serve a methodology to select the specific technologies for practical used of 3D printing.

Originality/value – Diverse predictions for 3D printing technology have been introduced in many academic and industrial fields. Most of them were made by subjective approaches depended on the knowledge and experience of the experts concerning 3D printing technology. So, they could be fluctuated according to the congregated expert groups, and be unstable for efficient R&D planning. To solve this problem, the authors study on more objective approach to predict the future state of 3D

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printing by analyzing the patent data of the developed results so far achieved. The contribution of this research is to take a new departure for understanding 3D printing technology using objective and quantitative methods.
Keywords 3D printing, Technology forecasting, Patent document, Statistical patent analysis, Technological evolution

Paper type Research paper

1. Introduction

Technology analysis is important for management of technology (MOT) fields such as R&D planning, technological innovation, new product development, etc. (Jun *et al.*, 2012; Roper *et al.*, 2011; Suh and Sohn, 2015; Wernz *et al.*, 2014). There are many resources for technology analysis (Cobo *et al.*, 2011; Goldman, 2014; Jeong and Song, 2014; Jun and Park, 2013). Papers and patents contain diverse information about recently developed technologies (Wong and Goh, 2012). In general, a journal paper contains the theoretical perspective of a technology. However, a patent has more practical information regarding a developed technology because the patent system exists to protect an inventor's exclusive right to his/her technologies over a period of time (Hunt *et al.*, 2007; Trappey *et al.*, 2011, 2012). Patent documents contain the inventor's name, application and issue dates, title, abstract, claims, drawings, figures, international patent classification (IPC) codes, citations, family patents, and so forth (Hunt *et al.*, 2007; Roper *et al.*, 2011). Hence, we can analyze technology efficiently using patent data.

We can analyze the technology related to given domain such as bio, nano, or three-dimensional (3D) printing using patent analysis or Delphi survey (Roper *et al.*, 2011). In general, there are three approaches to technology forecasting and analysis. They are based on the approaches of qualitative, quantitative, and combined by qualitative and quantitative. Many researches of technology analysis using these approaches have been studied in diverse fields (Geum *et al.*, 2015; Huang *et al.*, 2013, 2014; Jeong and Yoon, 2015; Jun and Lee, 2012; Jun *et al.*, 2012; Jun and Park, 2013; Keller and Gracht, 2014; Markmann *et al.*, 2013; Park and Suh, 2013; Petruzzelli *et al.*, 2015; Wong and Yap, 2012). The qualitative technology analysis is to analyze technology by the Delphi survey based on the domain expert's knowledge (Rowe and Wright, 2001). In comparison, the technology analysis by quantitative approach is based on statistics or machine learning algorithms (Jun *et al.*, 2012). In this paper, we apply the quantitative method of technology analysis to examine the technological evolution of 3D printing, because the forecasting and analysis of 3D printing technology are not yet studied, and the development of 3D printing technology is increasing rapidly and will significantly affect most industries (UK IPO Patent Informatics Team, 2013). The analytical results of 3D printing technology are required for R&D planning or technological innovation in 3D printing technology.

We retrieved all patent documents related to 3D printing technology from patent databases around the world. In our study, we perform trend analysis of 3D printing technology, and find the technology relations from the retrieved patent data using statistical methods and social network analysis (SNA). The goal of this paper is to examine the technological evolution of 3D printing technology using statistical patent analysis. The contribution of our research is to provide practical and meaningful results for R&D planning and technological innovation in the technology domain of 3D printing.

2. Research background

The technology of 3D printing creates 3D objects from digital design data (Stanic *et al.*, 2012; UK IPO Patent Informatics Team, 2013). Using this technology, we can create an item cheaply using a 3D printer. Hence, this technology is very useful to diverse industries such as small quantity batch production. The ability to print in 3D is changing the paradigm of manufacturing processes, that is, the technology is replacing traditional manufacturing system (Günther *et al.*, 2014). Using a digital design, the 3D printer makes an object layer-by-layer using a mixture of inks, plastics, or metals. This process is more efficient and cheaper than traditional manufacturing. If we have a 3D printer, we can create necessary objects anywhere in the world. Therefore, understanding the future state of 3D printing technology and its technological evolution is important to the fields of MOT such as R&D planning and new product development. We can analyze and forecast this technology using patent documents related to 3D printing technology because we can access detailed information about developed technology in the patents.

There were many research results for technology analysis. They can be divided into three approaches. The first methodology is to analyze and forecast technology by qualitative approach. This was originally based on Delphi technique using expert survey (Rowe and Wright, 2001). The qualitative approach have been researched and developed by variously modified methods in diverse fields (Hung *et al.*, 2013; Keller and Gracht, 2014; Markmann *et al.*, 2013; Rikkonen and Tapio, 2009). They used expert group with appropriate domain experience and knowledge for technology forecasting and analysis. Hung *et al.* (2013) performed strategic foresight the iPad's impact on Taiwan's person computer ecosystem using their modified Delphi technique, and they used frequency table and graphs for analyzing and summarizing the Delphi results. Markmann *et al.* (2013) suggested a risk analysis by Delphi for identifying and assessing future technological challenges in supply chain security. They developed the risk scenarios, and analyzed the risk for stakeholder perspectives. In addition, Keller and Gracht (2014) proposed a future foresight process to the influence of information and communication technology using Delphi survey. Because most previous approaches based on expert's experience and knowledge were subjective and qualitative, their results of technology analysis can be fluctuating and unstable according to selected group of experts. Also the Delphi is depended on gathering, using, and planning expert opinion through survey such as scenario analysis and technology roadmapping (Roper *et al.*, 2011). But this requires delicate and serious procedure because of managing expert group. If we use the well-chosen experts with relevant domain experience and knowledge, and perform the expert survey by the Delphi principles (Rowe and Wright, 2001), we can expect the reliable and meaningful results. In many tasks for technology forecasting and analysis, this approach is still considered and used.

To overcome the limitation and problem of the qualitative approach to technology forecasting and analysis, many studies on quantitative approach have been proposed (Eggers and Eggers, 2011; Geum *et al.*, 2015; Jun, 2012; Jun and Lee, 2012; Jun *et al.*, 2012; Jun and Park, 2013; Lee *et al.*, 2011; Park and Suh, 2013; Petruzzelli *et al.*, 2015; Subramanian and Soh, 2010). Most of them were based on statistics and machine learning algorithms for technology analysis, also they used patent or paper which contained the information of researched and developed technologies. In addition, the quantitative approach is relied on patent document analysis and text mining. Using this process for technology analysis, we can get the analytical results for technology forecasting, evolution, and innovation. Statistics and machine learning have provided valuable methods for analyzing patent data, such as regression, time series analysis, association rules, SNA, and K-means clustering. Eggers and Eggers (2011) studied on a choice-based conjoint adoption model to forecast green technology trends in automobile industry. They used a probabilistic model for technology forecasting. Geum *et al.* (2015)

developed data-driven technology roadmap using association rule mining that is popular statistical method. Jun (2012) forecasted the central technology for nano-technology field using SNA graph and measures. Jun *et al.* (2012) found vacant technology areas in MOT using technological matrix map and patent document clustering. Jun and Park (2013) analyzed Apple's entire patents using statistics, and examined the technological innovation of Apple's products such as iPod, iPhone, and iPad. Lee *et al.* (2011) performed a cluster analysis for the information and communication technologies, and they showed the technology clustering result based on evolutionary patterns using hidden Markov model. Park and Suh (2013) showed the technological knowledge flow and innovation using patent citation analysis. Petruzzelli *et al.* (2015) also used patent citations to estimate patent influence. They applied the estimated patent influence to new technology development. Subramanian and Soh (2010) found the relationship between science and technology in biotechnology industry using negative binomial regression. They demonstrated how the scientific capability affects to produce new technology. Most researches for the quantitative approach did not consider the domain expert's knowledge in the process of technology forecasting and analysis. But they needed some experience of the domain experts when the results of quantitative approach were applied to real problems such as R&D planning or technological innovation.

Because of the limitations of qualitative and quantitative approaches, some researches combined by two approaches were introduced (Huang *et al.*, 2014; Jeong and Yoon, 2015; Sun *et al.*, 2008; Wong and Yap, 2012). Huang *et al.* (2014) combined patent analysis (quantitative) and roadmapping (qualitative) for technology analysis. They mapped the science and technology planning to the technological development trends in the future. Jeong and Yoon (2015) developed the patent roadmap based on technology roadmap by patent keyword analysis (quantitative) and technology ontology (qualitative). Sun *et al.* (2008) extracted the pattern of environmental technology using patent-IPC code analysis (quantitative) and activity index (qualitative). In the combined approach, the proper combination between quantitative and qualitative approaches is not easy.

So there is no the best in three approaches which are qualitative, quantitative, and combined methods. According to the tasks of technology forecasting and analysis, we can select a suitable approach form qualitative, quantitative, and combined approaches. Table I shows the comparison of three approaches to technology analysis for technological evolution.

It is difficult to decide to decide which one is better than other approaches, because the three approaches have their strengths and weaknesses. So we have to select a proper approach according to the tasks for solution. In this paper, the task is to analyze and forecast the technology related to 3D printing. The technology of 3D printing has become relatively commonplace in recent years. The potential for technological development of 3D printing is constantly extended in the future as well. The 3D printing technology have been researched and developed in diverse areas as well as medicine (Dimitrov *et al.*, 2006; Giordano *et al.*, 1997; Günther *et al.*, 2014; Kim, 2014; Lee *et al.*, 2005; Sachs *et al.*, 1992; Seitz *et al.*, 2005; Stanic *et al.*, 2012). Most researches related to 3D technology were the technological developments for performing 3D printing. Few studies have analyzed the 3D technology itself for understanding the technological evolution of the 3D printing. In this paper, we use the patent documents related to 3D printing technology, and analyze the patent data for examining the technology evolution for 3D printing. So our research is based on the quantitative approach for technology forecasting and analysis. Next we show the proposed a methodology for understanding technological evolution for 3D printing technology.

Comparison	Qualitative	Quantitative	Combined
Approach	Subjective	Objective	Subjective + objective
Methodology	Using expert group with domain experience and knowledge	Analyzing patent, paper, or technical literature using statistics and machine learning	Analyzing collected data + validating and interpreting the analyzed result by domain expert
Analytical method	Delphi survey, Scenario analysis, Technology roadmapping, frequency table, graph, mean, and median	Text mining, regression, social network analysis, hidden Markov model, negative binomial regression, citation analysis	Qualitative + quantitative
Result	Future path foresight, strategic foresight, long-term decision making support, patent and technology roadmaps	Technology clustering and classification, technology roadmap, emerging and vacant technology, patent citation	Activity index, logistic growth curve, patent trend and changing pattern, patent roadmap based on technology roadmap, ontology of technology

Table I. Comparison of qualitative, quantitative, and combined approaches

3. Methodology of technology evolution for 3D printing

3.1 Trend analysis

The technologies related to 3D printing have been researched and developed rapidly in diverse domains. Hence, the analysis and identification of the technological trends in 3D printing are meaningful for understanding the evolution of this technology. Also the technological trend analysis of 3D printing forecasts the direction and speed of technological changes, and provides technological innovation for R&D planning. In this paper, we first consider time series regression (Bowerman *et al.*, 2005). Like most linear regression models, this consists of a dependent variable (Y) and independent variable (t) that represent the number of applied patents and time, respectively. Given data of the form (Y_1, t_1), (Y_2, t_2), …, (Y_n, t_n), the structure of a time series regression is:

$$Y_i = \beta_0 + \beta_1 t_i + \varepsilon_i, \quad i = 1, 2, \ldots, n \tag{1}$$

where (Y_i, t_i) represents the number of patents in year t_i, and ε_i is the error term at time i. The intercept and slope of the model are given by β_0 and β_1. In addition, we can determine the velocity of developments in 3D printing technology by slope β_1. The larger the value of β_1, the more quickly 3D printing technology is being developed. So, in trend analysis, two variables are used for time series regression model. The one variable is time itself, and this is applied year (t) of each patent. The other variable is the number of applied patents (Y) according to time (year). The result from trend analysis, we can find temporal and quantitative trends of development of 3D printing technology.

3.2 Association analysis

There are many methods for association analysis such as association rule mining, Bayesian networks, graph theory, or SNA. Association rule mining is a form of pattern mining that uses support and confidence measures based on conditional probability. A Bayesian network is a probabilistic network model that uses the conditional independencies between variables (Han *et al.*, 2012). Graph theory is another approach based on data structure for association analysis. In this paper, we use the SNA model for the association analysis of patent documents related to 3D printing. In general, a patent document is not structured data, and is hence not suitable for statistical methods or machine learning algorithms. Therefore, we must transform this unstructured data into structured data for statistical analysis and machine learning. A structured data set consists of rows and columns of patent document IDs and IPC codes, respectively, and each element represents the frequency of each IPC code.

IPC codes represent a hierarchical structure of technologies. In addition, one IPC code is assigned to one sub-technology (WIPO IPC, 2014). Hence, analyzing the IPC codes of patents related to 3D printing can be one approach to understanding the technological evolution of 3D printing. The next step is to create structured data for IPC code analysis. Figure 1 shows a patent-IPC code matrix (Jun and Lee, 2012) of the type that we use in this paper.

The rows and columns are patents and IPC codes, respectively, and the elements of the matrix are the frequency with which an IPC code occurs in each patent. To create an adjacency matrix (AM) for SNA, we preferentially convert the frequency values in the patent-IPC code matrix to Boolean values as follows:

Do $i = 1$ to n;
  Do $j = 1$ to p;
  If element of $FD\,[i, j]$ is larger than or equal to 1;
Then the element of $BD\,[i, j]$ is set to 1;
Else the element of $BD\,[i, j]$ is set to 0;
  End Do
End Do;

Here, the ranges of $FD\,[i, j]$ and $BD\,[i, j]$ are defined as follows:

$$0 \leqslant FD\,[i,j] < \infty,\ BD\,[i,j] = 0 \ or\ 1 \tag{2}$$

We next compute the AM that is used for the SNA input source. In this paper, we multiply $FD\,[i, j]$ by its transpose $BD^T[i, j]$ to get the following AM:

$$AM_{p\times p} = BD^T_{p\times n} \times BD_{n\times p} \tag{3}$$

where "×" is matrix multiplication and the matrix transpose is an operation that exchanges the rows and columns of a matrix. The AM includes the connecting information among IPC codes. Hence, we can obtain diverse SNA results from analyzing AM data. The AM in our analysis is structured as follows (Figure 2).

SNA is a network analysis that determines the relationships between social nodes, where a social node is represented by an IPC code in our research. We extract the association results among the IPC codes using SNA. In this paper, we consider the degree measures of SNA. The degree of an IPC code is the number of links that connect to it and is a measure of the importance of an IPC code (Jun, 2012; Lee and Jun, 2014). The SNA degree consists of an in-degree and out-degree. The in-degree is

$$FD_{n\times p} = \left(\begin{array}{cccc} & \text{IPC.1} & \text{IPC.2} \ \cdots & \text{IPC.}p \\ \text{Patent.1} & \ddots & \vdots & \cdot^{\cdot^{\cdot}} \\ \text{Patent.2} & \cdots & \textit{Frequency value} & \cdots \\ \vdots & & & \\ \text{Patent.}n & \cdot^{\cdot^{\cdot}} & \vdots & \ddots \end{array}\right)$$

Figure 1.
Patent-IPC code data

the number of incoming links, and the out-degree is the number of outgoing links. Using the degree values, we compute the betweenness and closeness centralities to understand the SNA results.

The betweenness measure computes the mediation of an IPC code between two IPC codes (Butts, 2008). That is, the increasing betweenness of an IPC code indicates that its technological importance is also increasing. This closeness measure is defined as the distance between two IPC codes (Butts, 2008). In addition, if the closeness between two IPC codes is larger than for others, then these nodes have a higher similarity to each other.

3.3 Principal component analysis (PCA) and PCA plots

In this paper, we consider PCA to cluster IPC codes using their correlation structure. Like the association analysis, we use the patent-IPC code data in Figure 1. The IPC codes of patent-IPC code data are used as original variables for PCA. Each principal component (*P*) is latent variable representing the original variables. In general, when most of the total variation of original variables can be explained by two, or three principal components, these components can replace all original variables without much loss of information (Johnson and Wichern, 1992). Using the variance-covariance structure between IPC codes, PCA explains the variation of original variables by their linear combinations (Johnson and Wichern, 1992). We build a principal component matrix using a linear combination of IPC codes as follows:

$$\begin{aligned} P_1 &= p_{11}IPC_1 + p_{12}IPC_2 + \cdots p_{1p}IPC_p \\ P_2 &= p_{21}IPC_1 + p_{22}IPC_2 + \cdots p_{2p}IPC_p \\ P_p &= p_{p1}IPC_1 + p_{p2}IPC_2 + \cdots p_{pp}IPC_p \end{aligned} \tag{4}$$

The first principal component (P_1) has the largest eigenvalue of all the principal components ($P_1, P_2, \ldots, P_p$), indicating that P_1 includes the largest information of original variables. In our research, we use the highest ranked two or three principal components for patent analysis. In addition, we construct a principal component plot to visualize the IPC codes. This plots all IPC codes on P_1 and P_2 and shows the clustering results of the IPC codes. We can then group IPC codes with other, similar IPC codes. The following figure shows an example of our PCA plot including five IPC codes.

In Figure 3, five IPC codes are located on the PCA plot by their principal component scores, and we can cluster the five IPC codes by this result. In this figure, we can conclude that IPC_1, IPC_3, and IPC_4 are assigned to same cluster, in addition, IPC_2 and IPC_5 are also grouped by another cluster. In this paper, we cluster all IPC codes related to 3D printing technology by PCA and PCA plot for technology analysis.

$$AM_{p\times p} = \left(\begin{array}{cccccc} & \text{IPC.1} & \text{IPC.2} & \cdots & \text{IPC.}p \\ \text{IPC.1} & \ddots & & \vdots & & \\ \text{IPC.2} & \cdots & & \textit{Result of matrix multiplication} & & \cdots \\ \vdots & & & & & \\ \text{IPC.}p & & & \vdots & & \ddots \end{array} \right)$$

Figure 2.
Adjacent matrix data

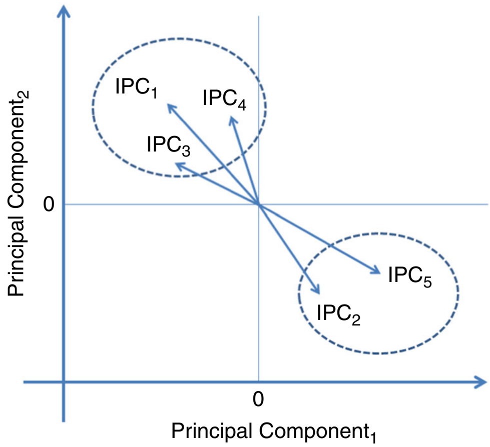

Figure 3.
PCA plot of five IPC codes

3.4 Technological evolution process

In this paper, we examine technological evolution of 3D printing using trend analysis, association analysis, and PCA. The following figure shows the technology analysis process for 3D printing (Figure 4).

In the proposed process, we collect the patent documents related to 3D printing, and extract IPC codes from retrieved patent data. To use statistical methods, we transform the IPC code data into patent-IPC code matrix and AM. Lastly the results of trend

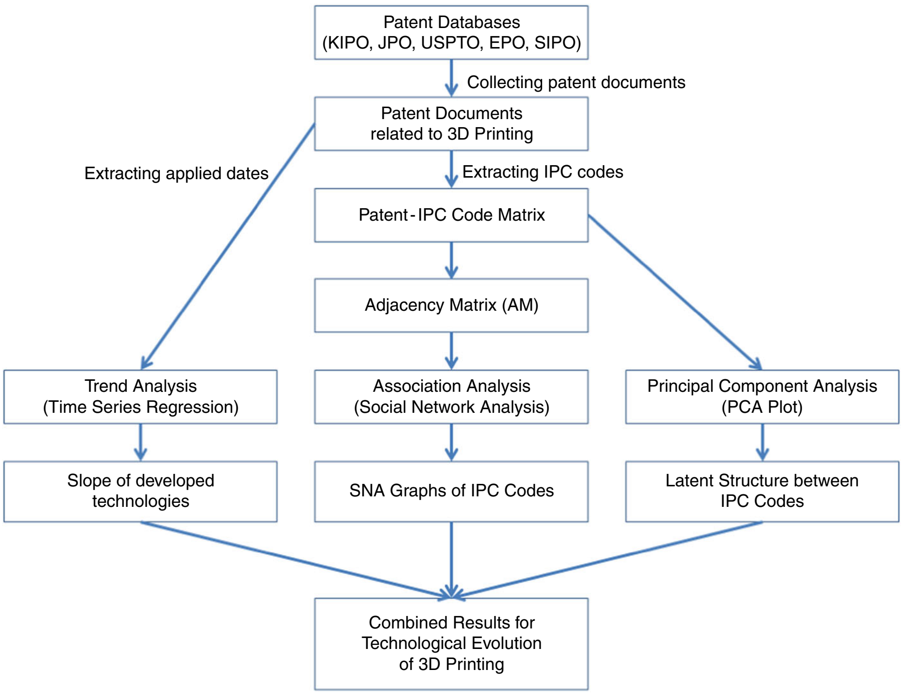

Figure 4.
Technology analysis process for 3D printing

analysis, association analysis, and PCA combine to examine technological evolution of 3D printing technology. Figure 5 shows the design that integrates our results.

In trend analysis, we estimate the velocity of technology development of 3D printing. Using this result, we can confirm the development possibility of 3D printing technology in the future. The result of SNA graphs provides the relational structure between sub-technologies of 3D printing. In addition, we can find the affecting and affected technologies as well as central technologies in 3D printing domain. According to the PCA plot, we perform the technology clustering of 3D printing. In the PCA plot, the similar sub-technologies are located on same PCA arrow (direction). The technologies with same direction have to be developed at the same time. But the technologies with opposite direction are substituted for each other. In this paper, we identify the growth potential of 3D printing technology using trend analysis, and construct the R&D planning map using SNA graphs and PCA plot. Using our R&D planning map, the companies related to 3D printing can build their R&D programs.

4. Results

We collected patent documents related to 3D printing from the Korean Intellectual Property Office (KIPO), Japan Patent Office (JPO), United States Patent and Trademark Office (USPTO), European Patent Office (EPO), and State Intellectual Property Office of the People's Republic of China (SIPO). In this paper, we retrieved the patent documents related to 3D printing technology from the FOCUST (2014) which is one of global patent search databases by using the following keywords.

We got the retrieved patent data as Excel file, and removed the duplicated patents by Excel macro programming. Also we drove the search terms in Table II by one of the authors of this paper. He has worked as an IP (intellectual property expert in the Korea Intellectual Property Strategy Institute (KIPSI), www.kipsi.re.kr). In Table II, we combined first and second keyword groups for retrieving correct patent documents related to 3D printing technologies. The keywords within group and between groups were conducted by "or" and "and" operations, respectively, for keyword equation. The total number of retrieved patents was 2,309. Table III shows the number of patents by year from 1980 to 2012.

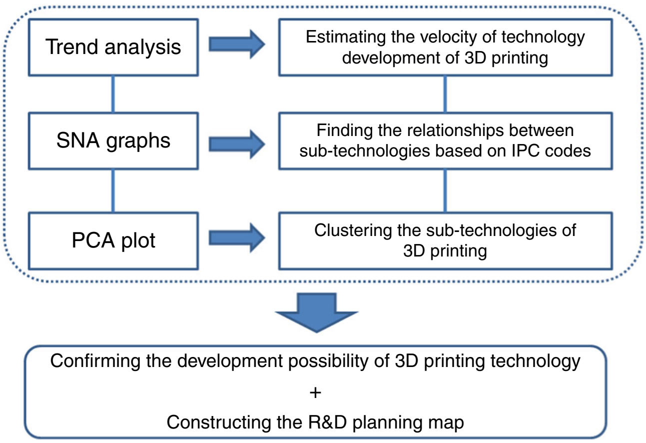

Figure 5. Design for integrating the results of trend analysis, SNA, and PCA plot

1st keyword group	2nd keyword group
3Dimension*, (3 OR three), threedimension*, 3D, print*	Acetal*, acrylonitrile*, additive*, alloy*, aluminium*, amides*, beam*, bio*, bioprint*, bronze*, butadiene*, carbonate*, cell*, cellprint*, ceramic*, chlorotrifluoro*, chromium*, cobalt*, compatible*, copper*, degradable*, direct*, electron*, etherimide*, ethylene*, eutectic*, fluoroplastic*, foil*, forming*, human*, hydrogel*, ink-jet*, "ink jet", iron*, laminated*, laser*, lithography*, manufacturing*, medical*, melting*, metal*, methyl*, moulding*, object*, orang*, orangprint*, organism*, oxide*, paper*, phenylene*, plaster*, plasterbased*, plastic*, poly*, polyacrylonitrile*, polyamides*, polycarbonate*, polyethylene*, polymer*, polyphenylenesulfide*, polypropylene*, polypthalamide*, polystyrene*, polysulfone*, polyvinylchloride*, powderbed*, prototype*, pthalamide*, rapid*, rapidprototype*, sculpture*, selective*, sintering*, stainless*, steel*, stereo*, structure*, styrene*, sulfone*, tetrafluoro*, thermo*, thermoplastic*, tissue*, tissueprint*, titan*, vinyl*

Table II. Keywords for retrieving correct patents

The first 3D printing patent was applied for in 1980. After the 2000s, the annual number of 3D printing patents has increased continuously. To identify this trend of increasing patent applications, we performed a time series regression for each decade. Before computing the regression parameters, we plotted the data by decade in Figure 6.

In this study, we used the R language for patent analysis (R Development Core Team, 2014). The upper left, upper right, and bottom right plots in Figure 6 show the number of patents by year for the 1980s, 1990s, and 2000s, respectively. The plot at the bottom right represents the number of patents by year for all decades. From this figure, we determined that the more recent rate of increase was faster than in earlier years. We estimated the regression parameters of the four plots to find more accurate rates. Table IV shows the estimated regression parameters.

In this result, the value of β represents the parameter of time series regression. The independent and dependent variables are year and number of patents, respectively. Hence, the β value is the positive slope of the time series regression model. That is, larger β values correspond with higher rates of applied patents.

Year	Number of patents	Year	Number of patents	Year	Number of patents
1980	8	1991	19	2002	105
1981	4	1992	22	2003	147
1982	2	1993	27	2004	126
1983	5	1994	44	2005	89
1984	6	1995	62	2006	130
1985	7	1996	57	2007	168
1986	3	1997	77	2008	184
1987	15	1998	41	2009	129
1988	23	1999	41	2010	147
1989	34	2000	91	2011	164
1990	47	2001	120	2012	146

Table III. Number of patents by year

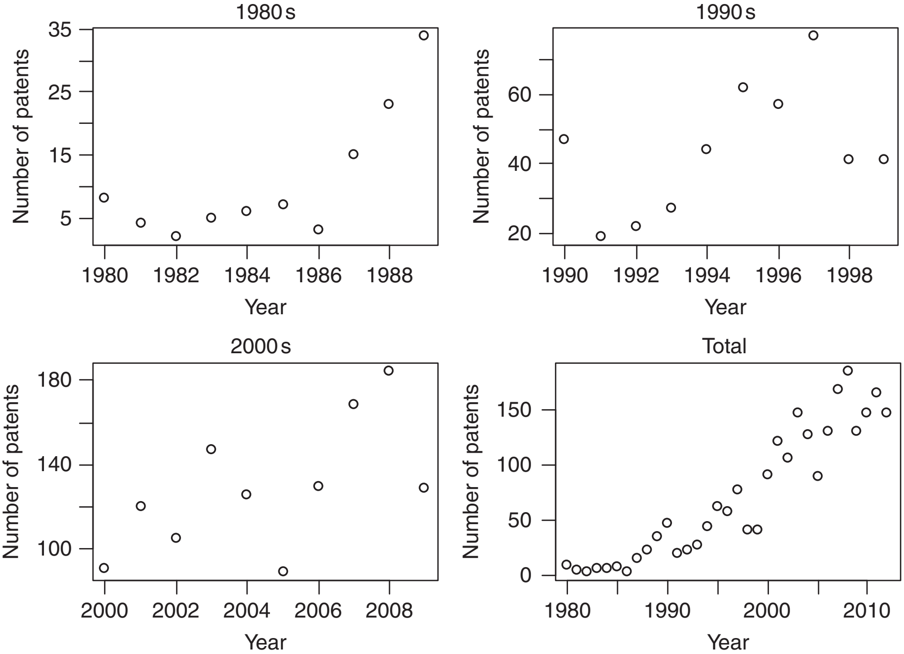

Figure 6.
Time series plots of applied patents

We computed the velocity of regression slope according to the time periods as follows:

$$Velocity_{1980\text{-}1989} = \frac{2.5879}{5.6444} = 0.4585$$

$$Velocity_{1990\text{-}1999} = \frac{2.9273}{5.6444} = 0.5186$$

$$Velocity_{2000\text{-}2009} = \frac{6.1636}{5.6444} = 1.0920$$

In this paper, the velocity is computed by the β value of each time period divided by the β value of total time period. We found the velocity was increased as time go on. So we can confirm the potential of growth of 3D printing technology.

To perform SNA graphs and PCA plot, we used IPC codes of the retrieved patents related to 3D printing technology. The IPC represents a hierarchical structure of the classification pf patents according to the technological areas (WIPO IPC, 2014). So using the IPC codes, we can perform efficient and effective patent analysis. Many

Table IV.
Estimated regression parameter

Regression result	Total	1980-1989	1990-1999	2000-2009
β	5.6444	2.5879	2.9273	6.1636
p-Value	0.0001	0.0115	0.1554	0.0642

researches of patent analysis using IPC codes were studied in diverse technology areas (Breitzman and Mogee, 2002; Dou, 2004; Dou *et al.*, 2005; European IPR Helpdesk, 2013; Jun, 2011; Jun and Lee, 2012; Kim *et al.*, 2015; Petruzzelli, 2011; Schmoch, 2008; Sternitzke *et al.*, 2008; Tseng *et al.*, 2007). They showed novel and meaningful results for technology forecasting and analysis. In the previous works (Dou *et al.*, 2005; Jun, 2011; Jun and Lee, 2012; Kim *et al.*, 2015; Petruzzelli, 2011; Schmoch, 2008; Sternitzke *et al.*, 2008; Tseng *et al.*, 2007), most studies on technology analysis used three-digit (three level) IPC code. So we also used this IPC code structure. In addition, the hierarchical structure of three-digit IPC code is shown by its technological hierarchy. For example, the IPC code of B29C is defined as follows:

B – Section: reforming operations; transporting.

B29 – Class: working of plastics; working of substances in a plastic state in general.

B29C – Subclass: shaping or joining of plastics; shaping of substances in a plastic state, in general; after-treatment of the shaped products, e.g., repairing.

The specific digit of IPC codes (e.g. B29C 31/06, H04J 1/20, etc.) represents more detailed technologies. On the contrary to this, the general digit of IPC codes (e.g. B, H, etc.) shows broader technologies. Therefore we need proper digit of IPC codes for efficient and effective technology analysis. To analyze IPC codes, we selected the analyzable patent documents based on their inclusion of IPC codes. Therefore, we extracted 204 IPC codes from the 2,309 selected patent documents. Among them, we used the top 20 IPC codes, as listed in Table V.

For this analysis, we used the R package "igraph" to perform SNA (Csardi, 2014). Using the above results, we generated the structured data matrix for performing SNA, as shown in Figure 7.

Each element of matrix D represents the frequency of the IPC code occurrence in the patent. We considered this data for the SNA of 3D printing technology. There are many methods to make adjacent matrix for SNA (Butts, 2008; Jun and Park, 2013; Jun and Lee, 2014). Jun and Park (2013) constructed the matrix using binary value, that is, if an

IPC code	Ranking	IPC code	Ranking
B29C	1	A61C	11
B41J	2	A61K	12
B41M	3	B28B	13
B32B	4	B05D	14
B22F	5	C09D	15
H05K	6	C08F	16
C04B	7	C08L	17
G03F	8	C22B	18
G06F	9	A61L	19
A61F	10	B22C	20

Table V.
Top 20 IPC codes for 3D printing

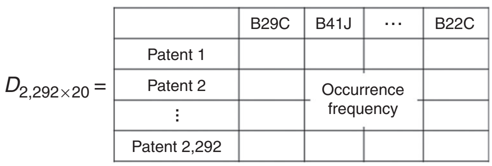

Figure 7.
Structured data matrix

IPC code is occurred in a patent, the element of the matrix is 1, otherwise its value is 0. Jun and Lee (2014) built an adjacent matrix using correlation structure between IPC codes. If the correlation coefficient of two IPC codes is larger than predetermined cutoff value then the element of adjacent matrix is 1, otherwise its element value is 0. But according to the change of the cutoff values the SNA graphs can be change. This is a problem in SNA. So in this paper, we made an adjacent matrix using the "igraph" (Csardi, 2014) for efficient and effective SNA graphs. First, we converted D to a Boolean matrix *D.Boolean*, and transformed this matrix into an IPC code to IPC code AM as follows:

$$D.adjacency = D.Boolean \times transpose\,(D.Boolean)$$

Matrix *D.adjacency* is computed by matrix multiplication of *D.Boolean* and its transpose. We then get the AM for the top 20 IPC codes, as shown in Figure 8.

Here, the diagonal elements represent the centrality and connecting degree. The larger this value, the more important the IPC code. Using *D.adjacency*, we built a general SNA graph, as shown in Figure 9.

This figure shows the unstructured association between IPC codes. Most IPC codes are connected to each other. Hence, we determined that most of the technologies related to 3D printing have been developed together. However, IPC code C22B is connected only to IPC code B22F. The technologies of codes C22B and B22F are "production or refining of metals; pretreatment of raw materials" and "working metallic powder; manufacture of articles from metallic powder; making metallic powder; apparatus or devices specially adapted for metallic powder," respectively (WIPO IPC, 2014). In addition, it is clear that the technology of IPC code B29C is key technology for 3D printing because it lies at the center of the SNA graph and is connected to many other IPC codes. This IPC code represents the technology of "shaping or joining of plastics; shaping of substances in a plastic state, in general; after-treatment of the shaped products, e.g., preparing" (WIPO IPC, 2014). To determine the density of this SNA graph, we computed the distribution of the SNA degrees (the summed in-degree and out-degree), as shown in Figure 10.

From this result, we concluded that the SNA graph was meaningful because most of the degrees were over 13. Hence, we performed additional analysis. To identify more detailed relationships between the IPC codes, we built an SNA graph with a circle layout, as shown in Figure 11.

This figure shows that IPC codes B28B, G03F, C04B, B22F, B32B, and A61L are highly connected to other IPC codes. By this SNA graph, we confirmed our conclusion from Figure 8. In this study, we generated an additional SNA graph with the Reingold-Tilford layout based on tidier tree drawings (Csardi, 2014; Reingold and Tilford, 1981). Reingold and Tilford (1981) introduced an algorithm for producing tidier drawings by storage requirement as well as comparable time. Using this layout, we can find general graph structure because the graph shows major networking from entire graph structure. This graph illustrates the hierarchical structure of the relationships between the IPC codes, as shown in Figure 12.

We can see from this graph that the technology based on B29C is the most fundamental technology in 3D printing and the technologies from B41J to B22C are the next most basic technologies. The C22B technology is last level of technology for 3D printing. Using this result, we can plan an R&D process for 3D printing, that is, to have

	B29C	B41J	B41M	B32B	B22F	H5K	C4B	G3F	G6F	A61F	A61C	A61K	B28B	B5D	C9D	C8F	C8L	C22B	A61L	B22C
B29C	835	149	58	91	103	41	71	64	55	63	27	53	96	27	31	48	41	0	32	55
B41J	149	309	38	30	29	27	9	2	17	0	8	0	35	4	13	0	4	0	0	0
B41M	58	38	232	19	0	5	7	23	0	10	6	0	1	16	33	35	7	0	0	0
B32B	91	30	19	211	43	32	5	1	16	3	0	2	27	20	0	1	20	0	1	16
B22F	103	29	0	43	165	26	11	0	16	5	0	0	43	5	0	0	5	1	3	24
H5K	41	27	5	32	26	159	0	21	10	0	0	0	26	2	2	0	2	0	0	0
C4B	71	9	7	5	11	0	150	1	1	21	16	0	47	5	6	0	2	0	3	1
G3F	64	2	23	1	0	21	1	141	6	2	0	0	0	0	10	26	5	0	8	7
G6F	55	17	0	16	16	10	1	6	140	7	2	0	1	0	0	0	3	0	1	16
A61F	63	0	10	3	5	0	21	2	7	138	7	15	0	2	6	0	0	0	39	27
A61C	27	8	6	0	0	0	16	0	2	7	135	56	0	0	6	0	8	0	2	0
A61K	53	0	0	2	0	0	0	0	0	15	56	119	0	4	0	0	10	0	15	0
B28B	96	35	1	27	43	26	47	0	1	0	0	0	117	7	0	1	3	0	1	2
B5D	27	4	16	20	5	2	5	0	0	2	0	4	7	95	19	1	0	0	1	0
C9D	31	13	33	0	0	2	6	10	0	6	6	0	0	19	85	3	11	0	7	7
C8F	48	0	35	1	0	0	0	26	0	0	0	0	1	1	3	74	7	0	1	1
C8L	41	4	7	20	5	2	2	5	3	0	8	10	3	0	11	7	72	0	2	0
C22B	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	71	0	0
A61L	32	0	0	1	3	0	3	8	1	39	2	15	1	1	7	1	2	0	69	15
B22C	55	0	0	16	24	0	1	7	16	27	0	0	2	0	7	1	0	0	15	67

Figure 8.
Adjacency matrix between top 20 IPC codes

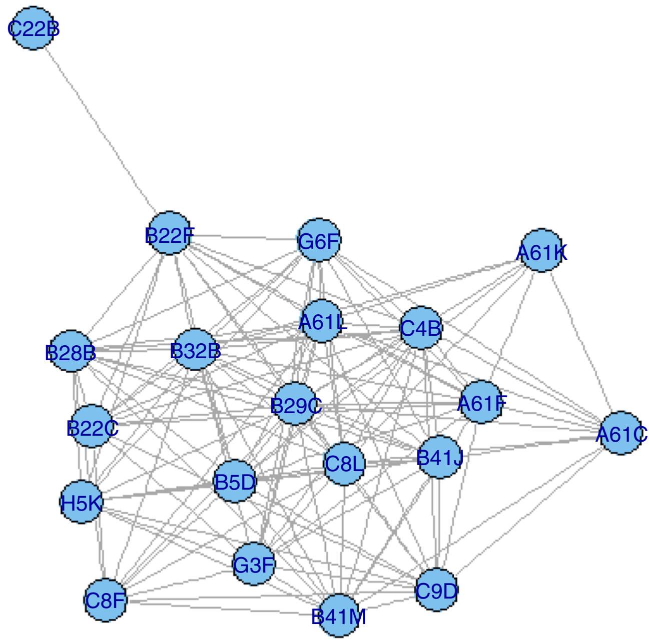

Figure 9.
SNA graph: random layout

competitiveness in the 3D printing industry, we should acquire technology based on B29C. Figure 13 shows the SNA graph with an emphasis layout.

The font size of an IPC code represents its technological importance; hence, larger character sizes for the IPC code indicate a more important technology. From this result, we could arrange B29C, B32B, A61L, C04B, C08L, B41M, B28B, etc. in order of font size. In this paper, Figures 8, 10-12 were built from same AM data, but they showed different graph structures. We made diverse SNA graphs to understand the relationships between IPC codes efficiently and clearly. Most of the explanation of

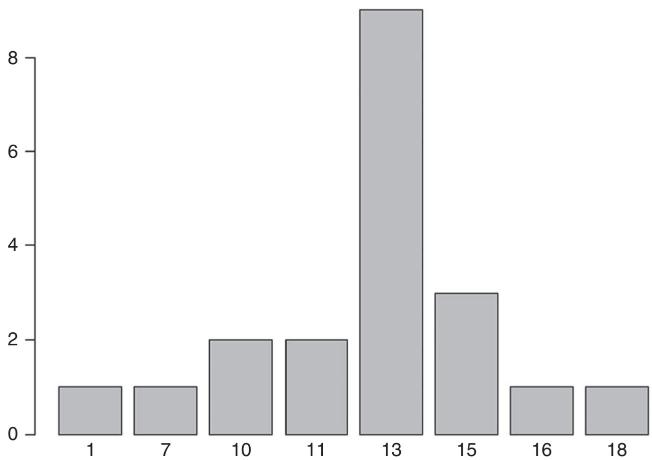

Figure 10.
Distribution of SNA degrees

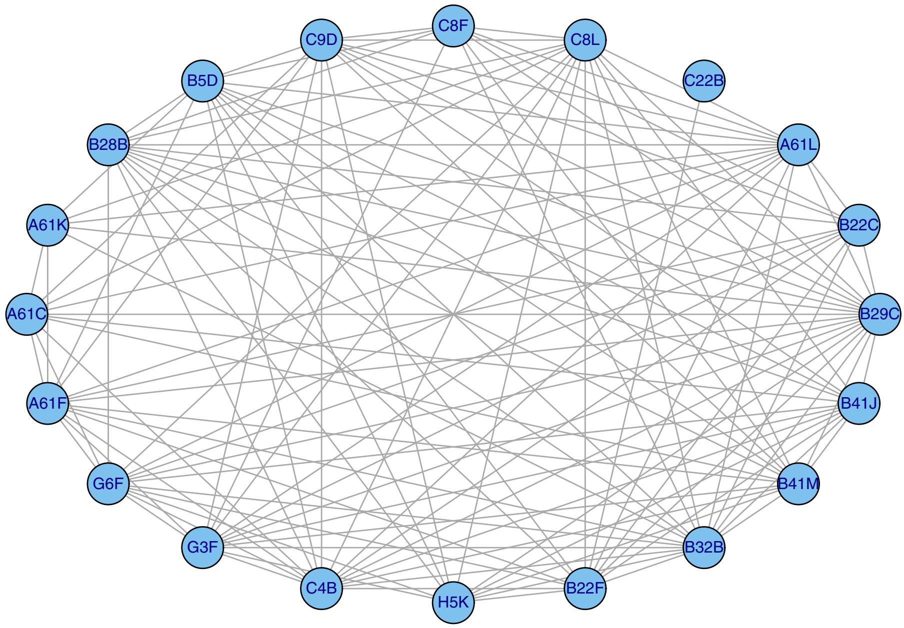

Figure 11.
SNA graph:
circle layout

graph structure was represented in first SNA graph (Figure 8). We confirmed the conclusion of the first graph by using next three graphs (Figures 10-12). To perform a more detailed technology analysis, we selected the top ten IPC codes of the 3D

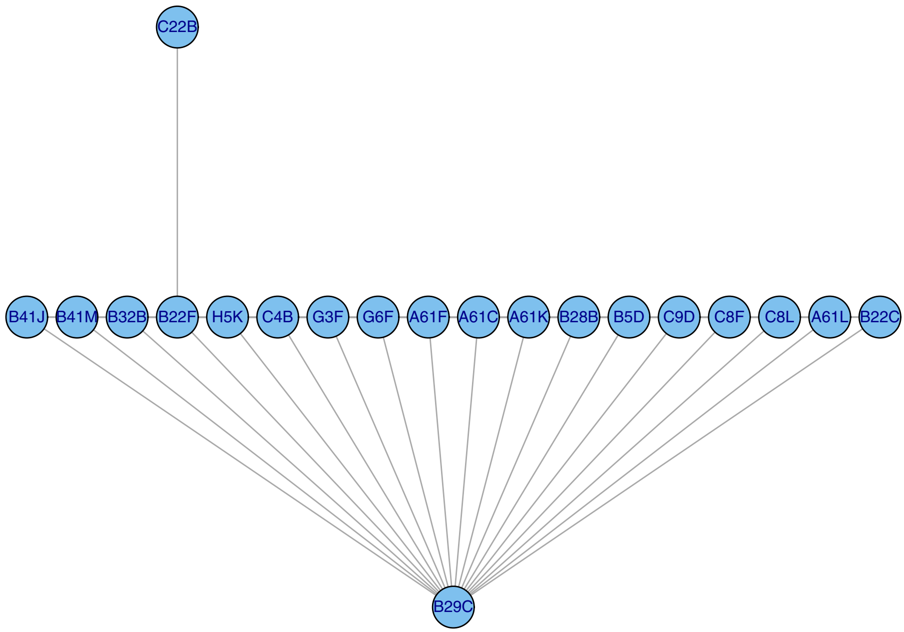

Figure 12.
SNA graph:
Reingold-Tilford
layout

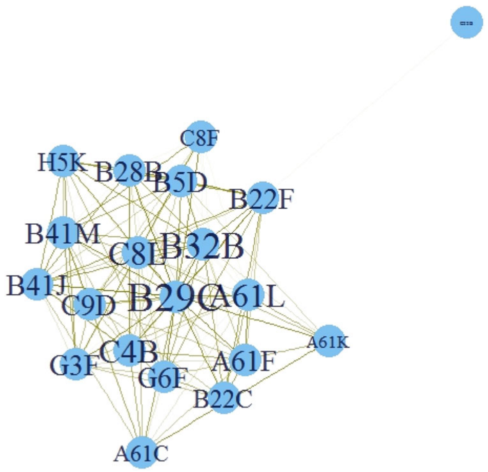

Figure 13.
SNA graph:
emphasis layout

printing patents. Table VI shows the IPC codes and their technological descriptions (WIPO IPC, 2014).

Using the top ten IPC codes, we built three SNA graphs. Figure 14 shows an SNA graph based on a random layout. In our research, this is basic SNA graph.

In Figure 13, we determined that IPC codes B29C and B32B were more connected than the rest of the IPC codes. Using this result, we can support the result of the first SNA graph from all IPC codes in Figure 8. We also built another SNA graph using a circle layout, as shown in Figure 15.

Rank	IPC code	Technology description
1	B29C	Shaping or joining of plastics; shaping of substances in a plastic state, in general; after-treatment of the shaped products, e.g., repairing
2	B41J	Typewriters; selective printing mechanisms, i.e., mechanisms printing otherwise than from a form; correction of typographical errors
3	B41M	Printing, duplicating, marking, or copying processes; color printing
4	B32B	Layered products, i.e., products built-up of strata of flat or non-flat, e.g., cellular or honeycomb, form
5	B22F	Working metallic powder; manufacture of articles from metallic powder; making metallic powder; apparatus or devices specially adapted for metallic powder
6	H05K	Printed circuits; casings or constructional details of electric apparatus; manufacture of assemblages of electrical components
7	C04B	Lime; magnesia; slag; cements, compositions thereof, e.g., mortars, concrete or like building materials; artificial stone; ceramics; refractories; treatment of natural stone
8	G03F	Photomechanical production of textured or patterned surfaces, e.g., for printing, for processing of semiconductor devices; materials therefore; originals therefore; apparatus specially adapted therefore
9	G06F	Electric digital data processing
10	A61F	Filters implantable into blood vessels; prostheses; device providing patency to, or preventing collapsing of, tubular structures of the body, e.g., stents; orthopedic, nursing or contraceptive devices; fomentation; treatment or protection of eyes or ears; bandages, dressings or absorbent pads; first-aid kits

Table VI.
Top ten most frequently occurring IPC codes

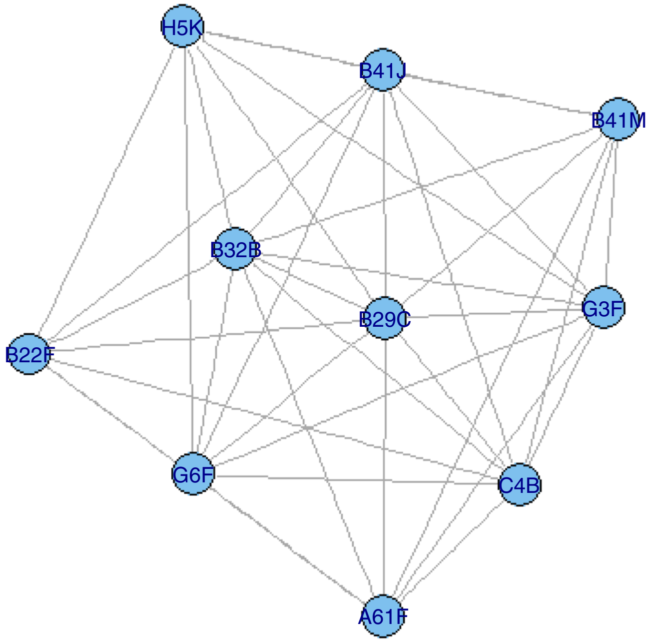

Figure 14.
SNA graph using top ten IPC codes: random layout

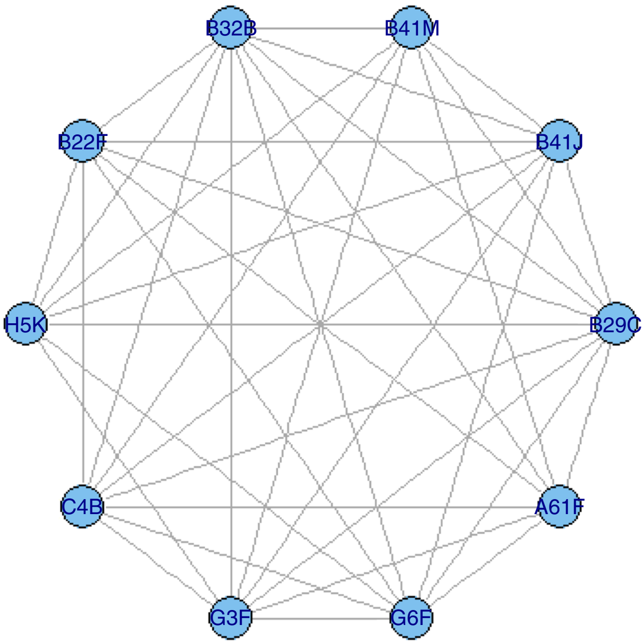

Figure 15.
SNA graph using top ten IPC codes: circle layout

We also confirmed the result of the SNA graph using a random layout. To understand the hierarchical structure of IPC codes, we used the Reingold-Tilford layout to construct an SNA graph. Figure 16 shows this SNA graph.

We determined that IPC code B29C was the only highly ranked IPC code in 3D printing technology. Figures 13-15 can be interpreted as previous SNA graphs (Figures 8, 10-12). In Figure 13, we explained most descriptions about graph structure of top ten IPC codes. To determine the relationship between IPC codes, we generated a PCA plot using the principal component scores of the IPC codes, as shown in Figure 17. For understanding the visualization of PCA plot, we constructed two-dimensional plot, because we have trouble to understand the visualization according to increasing the dimension. In addition, Johnson and Wichern (1992) showed the proper values for the number of principal components are two or three. In general PCA, this means that two or three principal components have sufficient variation (explanation) of entire variables.

This PCA plot was constructed using the first and second principal components and their scores. This plot contains the total patents and all IPC codes arranged by their PCA results. As mentioned in Section 3.4, we can cluster the IPC codes using the arrows and its direction in the PCA plot. The IPC codes located on or near same arrows are the technologies they need each other. That is, they have to be developed together at the same time. But the IPC codes located in opposite arrow directions are the technologies they are alternated each other. For example, in two IPC codes are located in opposite direction arrows, respectively, if one IPC code based technology is developed, then the other IPC code based technology is not necessary to be developed. From this, we can conclude that the directions of B29C and B41M are in opposition. This means that the development of B29C technology makes B41M technology

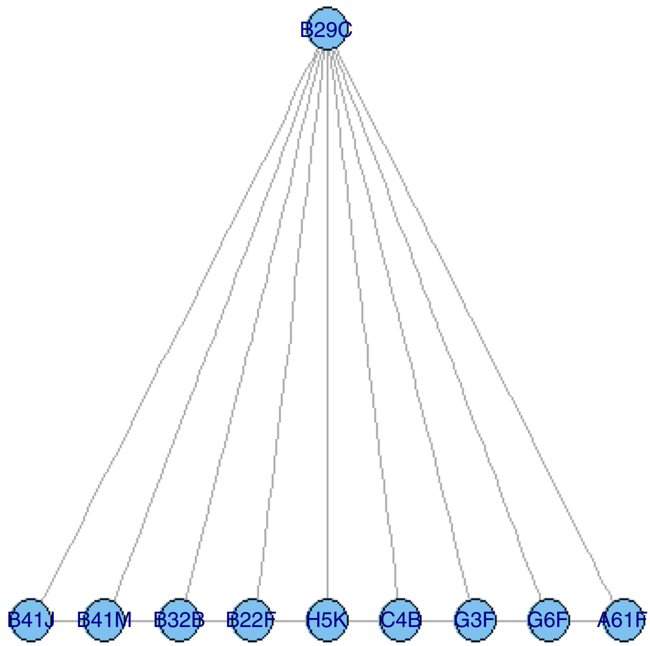

Figure 16.
SNA graph using top ten IPC codes: Reingold-Tilford layout

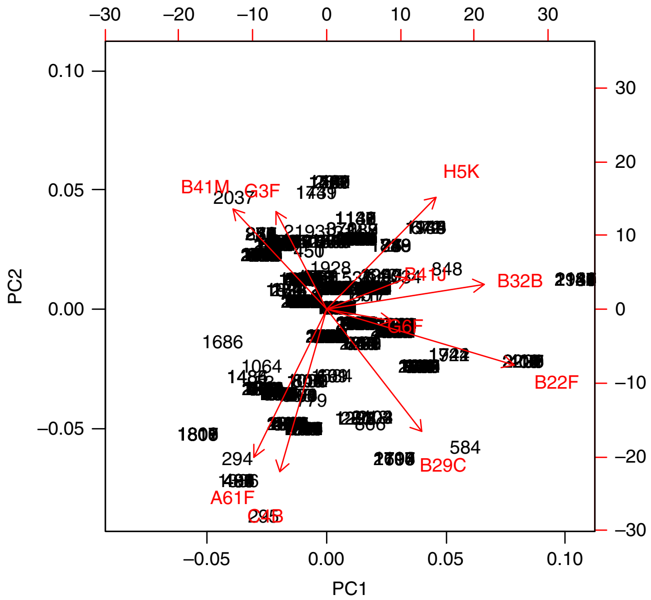

Figure 17.
PCA plot using the top ten IPC codes

redundant. The directions of A61F and C04B are similar, and this means that the two technologies should be developed together. There are differences of degree, B22F, G06F, C04B, A61F, and B32B are lying in the same direction with B29C. That is, the technologies based on them are needed to develop B29C technology. Therefore, we can conclude the technology of B29C is important technology for 3D printing, and the technologies of B22F, G06F, C04B, A61F, and B32B are necessary for developing B29C technology.

To apply our research result to R&D planning practically, we used the technology classification of 3D printing as follows (Kim, 2014); laser heating coagulation (LHC), fused deposition modeling (FDM), metal powder and laser sintering (MP&LS), photo fabrication (PF), laminated paper and binding (LPB), electron beam and metal powder melting (EB&MPM), Powder bed and plastic base (PB&PB), ink-jet (IJ), extra 3D printing technologies (EX). Using all results of trend analysis, SNA, and PCA, we built R&D strategy for 3D printing technology in Figure 18.

From the result of trend analysis, we confirmed the growth potential of 3D printing technology. Also we found that the IPC codes of B41M, B29C, and G03F represent the

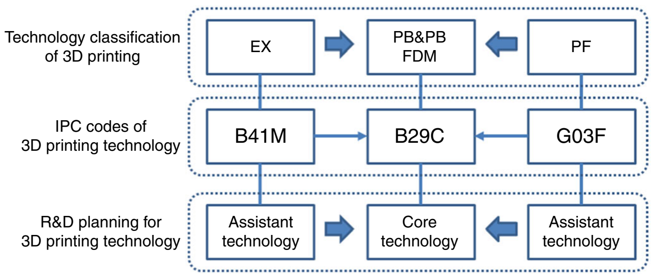

Figure 18.
Constructed R&D planning map

core technologies for 3D printing technology, and the technologies of B41M and G03F affect the technological development of B29C from the results of SNA graphs and PCA plot. We can assign B29C technology to "PB&PB" and "FDM" in technology classification of 3D printing. Also the technologies of "EX" and "PF" are connected to B41M and G03F, respectively. From the results, we knew that the technology of B29C was important to 3D printing. In addition, the technologies of B41M and G03F are applied to develop B29C technology. So in R&D planning for 3D printing, we need to develop the technologies of "PB&PB" and "FDM" via developed technologies based on "EX" and "PF."

5. Conclusions

In this paper, we demonstrated a methodology for analyzing the technological evolution of 3D printing. Our research was based on quantitative patent analysis, and we used IPC codes from the retrieved patent documents related to 3D printing technology. We transformed the collected patents into a structured data set and applied time series trend analysis, association rules, and PCA to analyze the data set. From the results of technology analysis, we determined that most technologies for 3D computing depend on the technology of B29C. The World Intellectual Property Organization (WIPO) defines this technology as "shaping or joining of plastics; shaping of substances in a plastic state, in general; after-treatment of the shaped products, e.g., repairing." However, the technologies of B41M and G03F were less related to the technology of B29C. In addition, according to WIPO, the technologies of B41M and G03F are "printing, duplicating, marking, or copying processes; color printing" and "photomechanical production of textured or patterned surfaces, e.g., for printing, for processing of semiconductor devices; materials therefore; originals therefor; apparatus specially adapted therefore." Hence, we should research theory and develop technology focussing on the B29C technology. Furthermore, there is less need to prioritize the B41M and G03F technologies. In addition, researchers and developers can use additional results from this paper.

This research can be used to the R&D planning for the development of 3D printing technology. In this paper, we tried our efforts to analyze the IPC codes from retrieved patent documents related to 3D printing technology. We only focussed on the view of IPC code for examining technological evolution of 3D printing. We did not consider the expert's view for understanding the results of technology analysis. But we know that the knowledge and experience from the experts related to 3D printing are also important to understand 3D printing technology. Our research contributes to novel methodology for examining technological evolution and analysis by using quantitative approach (IPC code analysis) and objective data source (patent documents). This research cannot cover all aspects of 3D technologies because we focussed on an objective approach to technology analysis. Therefore adding our result to practical fields efficiently is the roles of those who are engaged in practical domains related to 3D printing industry. In our future work, to overcome the limitation of our current work and make more advanced model for technological evolution, we will study on diverse text mining techniques and advanced statistical and machine learning methods using text data as well as IPC code of patent documents.

The 3D printing technology has a big impact on the global society and the economy. To understand the evolution of 3D printing technology is important and meaningful for developing most industrial fields such as manufacture, environment, medicine, information and communication, etc. Also the 3D printing technology will become a new industrial revolution with profound implications in the politics, economy, society, science, and engineering.

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