The Identification of Emerging Technologies of Automotive Semiconductor

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Abstract

As the paradigm of future vehicles changes, the interest in automotive semiconductor, which plays a key role in realizing this, is increasing. Automotive semiconductors are the technology with very high entry barriers that require a lot of effort and time because it must secure technology readiness level and also consider safety and reliability. In this technology field, it is very important to develop new businesses and create opportunities through technology trend analysis. However, systematic analysis and application of automotive semiconductor technology trends are currently lacking. In this paper, U.S. registered patent documents related to automotive semiconductor were collected and investigated based on the patent's IPC. The main technology of automotive semiconductor was analyzed through topic modeling, and the technology path such as emerging technology was investigated through cosine similarity. We identified that those emerging technologies such as driving control for vehicle and AI service appeared. We observed that as time passed, both convergence and independence of automotive semiconductor technology proceeded simultaneously.

Keywords: Emerging technology, Patent Analysis, LDA Analysis, Topic Modeling, Cosine Similarity

A preliminary version of this paper was presented at APIC-IST 2022, June 19-21, Gangneung, South Korea and was selected as an outstanding paper. This version changes patent type and collection period and includes cosine similarity analysis for investigating emerging technologies in automotive semiconductor industry.

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1. Introduction

As global traffic safety regulations have been stricter, and social and economic phenomena such as the pandemic and carbon neutrality are interlinked, consumer perception and demand for automobiles are rapidly changing. Against this backdrop, future vehicles are changing the way people and things move and are evolving from a means of transportation to a portable living space. Automotive semiconductors play a key role in realizing the functions of future vehicles, because they are being developed to enable various functions such as connected, autonomous, sharing & service, and electrics. To this end, it is necessary to develop and advance technologies such as sensors, communication, artificial intelligence, and driving control [1-4]. Automotive Semiconductors can be said to be a catalyst of growth that enables not only innovation in vehicle technology such as automobile safety and service, but also new cultural and social trends. In particular, as the technology required for future vehicles becomes more complex, the demand for automotive semiconductors will steadily increase, and both vehicles and semiconductors will become long-term growth engines from an industrial point of view [5]. On the other hand, unlike other semiconductors, automotive semiconductors have very high entry barriers due to their unique characteristics. Autonomous driving and eco-friendly vehicles require much more semiconductors than general internal combustion engine vehicles, and it is difficult to achieve the economy of scale because the automotive semiconductor specifications required for each vehicle model are different. In addition, it is a technology that requires high performance in temperature, humidity, and lifespan for safety reasons, and must satisfy international standards and standards for each automaker. It takes a lot of effort and time for automotive semiconductors to secure safety and reliability as well as technological level of completion. The future growth potential and characteristics of automotive semiconductors and the high interest of the industry are changing the technology level and demand patterns for automotive semiconductors. In addition, the innovation of semiconductor technology for the demand of future vehicles is affecting the restructuring of value chains and business models throughout the industry. The technology is continuously evolving not only by R&D, but also by industry and consumer demand, and companies are trying to intrinsically understand the evolution of technology for business [6]. Automotive semiconductor technology began to be applied to devices necessary for vehicle driving in the 1980s and 1990s. Since 2000, it has been applied in earnest not only to driving, but also to fuel economy improvement, safety enhancement, and convenience devices. The scope of its application field is now expanding to autonomous driving, driver assistance system, artificial intelligence, sensor, power, service and security [2, 7-17]. The technology advances further as for data processing speed and reliability. The role of automotive semiconductor technology has expanded to implement innovative technologies of next-generation transportation means such as autonomous shuttles and flying cars [18-20].

Technology trends are not just for identifying trends, but for pioneering new businesses and creating new business opportunities by predicting future technologies. In addition, for companies whose technology is the core, adaptation to rapid environmental changes, preoccupation with future technologies, and securing intellectual property are emerging as important factors for survival. Because of characteristics of automotive semiconductor compared to other semiconductors, it is very important to plan for strategies of new technology development and business by understanding technology trends. On the other hand, systematic analysis of automotive semiconductor technology trends is still lacking. This paper intends to analyze the trend of automotive semiconductor technology and the emerging technology and deduce new evolutionary direction.

This study consists of a total of 5 chapters. Chapter 2 examines prior research on emerging technologies and topic modeling based on patents. In Chapter 3, the research method is presented, and in Chapter 4, the core technology topics for automotive semiconductors by period are identified, and the emergence and convergence of technology and the path of technology are investigated. Finally, the conclusions, limitation and future works are given.

2. Literature Review

2.1 Emerging Technology

The term "emerging technology" has been frequently used in many studies. However, various concepts of emerging technology are used, and there are no standard or metrics for it [21-23]. For the reason, there are many different methods and approaches to study emerging technology; Future-oriented technology analysis in Nano technology [21], Fisher-Pry diffusion model in OLED TV [24], Bayesian clustering in humanoid robot [25], Scenario analysis in autonomous vehicles and energy field [26], Delphi in energy technology [27], Bibliometric analysis in internet of things technology [28], Technology keyword [29], Data envelopment analysis in battle tank technology [30]. Recently, many studies on emerging technologies have been active by combining patent analysis with various methodologies; patent analysis [31], Delphi and patent analysis [32], trend and patent analysis [33], patent and topic modeling [34]. This is due to the data characteristics of the patent as an information source. Patents include detailed descriptions of technologies based on a systematic classification system such as IPC (International Patent Classification) for a great part of technical fields and provide objective information. Studies using patent analysis are useful not only for simple technical information, but also for the research on technological competitiveness and technology development direction. In addition, it is used as an objective indicator to identify trends in technological development and change and establish innovation strategies such as corporate and national R&D direction design, investment, and business strategy [22, 31].

2.2 Topic modeling based on patents using LDA

Topic modeling related on Latent Dirichlet Allocation (LDA) in which we used for analysis is a probabilistic model for discovering abstract topics occurring in unstructured data as one of the data mining methodologies [35]. Topic modeling was initially used for the Latent Semantic Analysis (LSA) [36]. Then, LSA is improved by Hofmann et al. [37] to the Probabilistic Latent Semantic Analysis (PLSA) model. After Blei et al. [35] proposed the LDA, the LDA model or the LDA variant models are mainly used. The topic modeling which processes classification of patents, have been worked actively because of its ability to discover and present latent topics automatically.

Recently, research aiming to analyze emerging technologies using patent data and topic models and to derive technology trend analysis, technology opportunity development, and R&D strategies based on this is being actively conducted. In the study of Momeni et al. [38], they analyzed emerging technology using k-core and LDA analysis. They collected patent data between 1978 and 2012 from European Patent Office Worldwide Patent Statistical Database (PATSTAT). They limited the scope of patents selecting keywords "photovoltaic" and "solar cell" and IPC class H01L 31/00. They used extended patent family for collecting all. They find thin-film technology is probable to displace the dominant technology, in other words crystalline silicon. Furthermore, they identify emerging(hidden) technologies such as multijunction technology et al. in the photovoltaic industry. Based on LDA and about 160,000 of the United States Patent and Trademark Office (USPTO) full-text patents between 2001 and 2014 from the leading telecommunication firms, Suominen et al. [39] analyzed the dynamics of emerging technology and the evolution of knowledge profiles of industry leaders about technology strategies both hardware and software. They discussed implications for strategic management in firms and policy makers. To examine overall biometric technology trends, Lee et al. [40] used patent data. They extracted 37,462 patent documents between 1990 and 2016 at the big five patent offices using PATSTAT database. To verify annual trends, they applied LDA analysis to the abstracts of patents. They identified emerging technologies, such as fingerprint-enabled car anti-theft systems, discovered emerging topics and patent applicants, and provide practical insights to biometric industry stakeholders. Garzaniti et al. [41] analyzed technology trend in new space missions using LDA analysis based on patent data. They collected 933 patent documents to two hundred organizations which worked actively in the development of products and services in the missions of New Space area. They identified ten major topics and named “Flying/launch systems” et al. and technology trends for the future development of New space area based on the insights obtained by their survey of literature and patent. In recent years, hydrogen technology has attracted great public attention as a new energy technology because of its high potential to change existing energy technology. On the other hand, hydrogen technology is difficult to do analysis because of a broad range of themes such as hydrogen production, storage, distribution, and utilization. To verify this problem, Chen et al. [42] used topic modeling, classification, and time series analysis. They collected 17,281 patents in hydrogen technology area from USPTO from 2010 to 2019. They identified various hydrogen technology topics and compared the technology portfolios of key countries.

As a result of analyzing related works, it is possible to classify and identify emerging technology trends for the automotive semiconductor industry and technology by using patent data applied to the actual industry and analyzing it through a topic modeling, and establish a technology strategy.

3. Methodology

3.1 Research Model

For this study, to analyze and verify the key technology trends in the automotive semiconductor field, the research model is shown in **Fig. 1**.

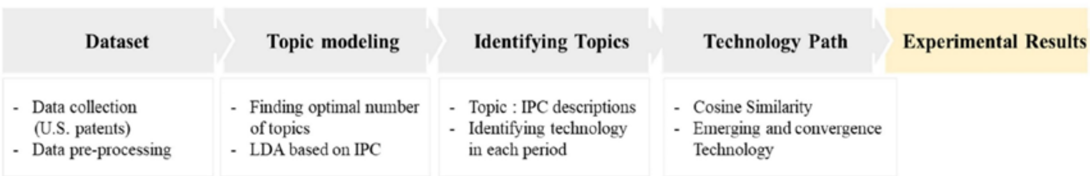

Fig. 1. Graphical presentation of our methodology

For the automotive semiconductor technology, patent documents are collected from the registered patents of the USPTO. The collected patents are analyzed mainly by IPC. The patent documents and those IPCs were properly preprocessed to prevent analysis errors such as validity and omission of information. For LDA analysis the optimal number of topics is determined, and LDA analysis based on IPC is performed. Based on the derived topics, the IPC constituting each topic is analyzed. After that, main technologies are identified and the trend of automotive semiconductor technologies are analyzed. And by using the cosine similarity between the identified topics, the trend of technology was investigated, and the emerging and convergence of technology was analyzed.

3.2 LDA

For this study, we applied LDA method, one of the representative topic modeling. LDA is a generative probabilistic mode that judges the existence of a topic latent in each document for a given document group based on the Dirichlet probability distribution [35].

LDA process is shown in **Fig. 2**. α and η are hyperparameters, and β is a parameter of Dirichlet probability distribution determined by η, which is the word generation probability for each topic. The word observed in the document w is generated from the topic, and the topic ratio θ at which the corresponding document is generated is a value that follows the Dirichlet distribution and is determined by the α value. z is determined from θ as the topic ratio for each document. k is the number of topics, M is the total number of documents, and N is the number of words. That is, when k topics are determined for M documents composed of N words, the topic ratio θ is determined by the α value, and z, which is a value representing the topic of each word, is determined by θ. In addition, the β value, which is the word generation probability for each topic, is determined according to the η value, and finally the document w, which is a set of N words, is determined by z and β. Since a document set is composed of topics and a topic is composed of words, it is possible to estimate the distribution of words and topics for a document and repeat this process to identify topics constituting the document set.

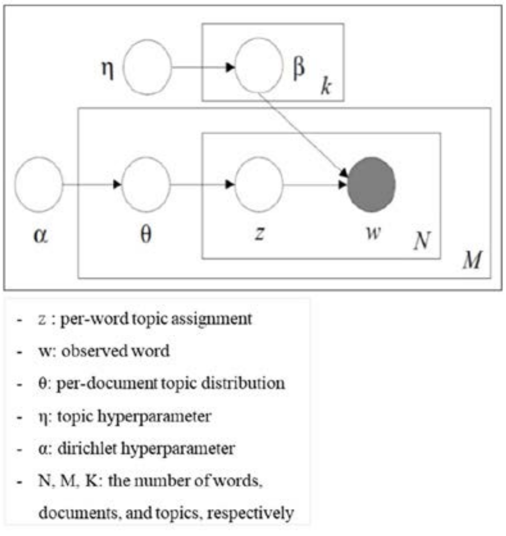

Fig. 2. Graphical model of LDA [35]

4. Experiments

4.1 Datasets

To collect patents, the search formula is "Semiconductor*Vehicle*Automotive". The collection period is from January 2012 to December 2020, and it is collected through WIPS (Worldwide Intellectual Property Service, www.wipscorp.com). The total number of collected patents is 14,670. To prevent analysis errors due to data duplication, omission, validity, etc.

among the collected patents, the data is removed and a total of 14,539 patents are used for analysis. Collected patents are divided by period, named P1(Jan. 2012 – Dec. 2014), P2(Jan. 2015 – Dec. 2017) and P3(Jan. 2018 – Dec. 2020). The number of patents is 1,606 documents of P1, 5,287 documents of P2 and 7,646 documents of P3. As shown in **Fig. 3**, the number of patents is continuously increasing.

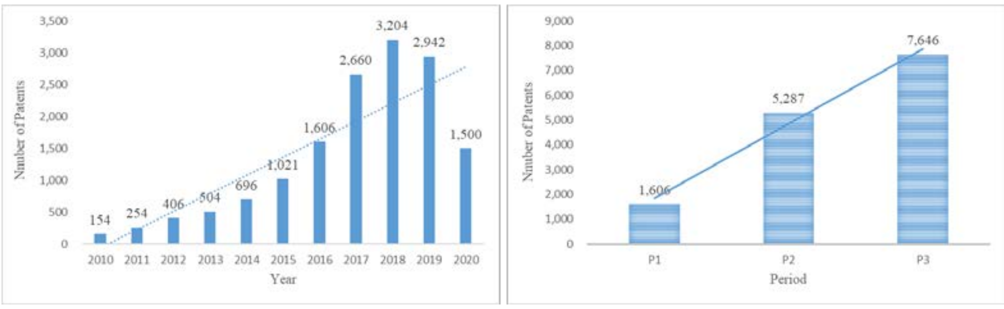

Fig. 3. The number of collected Patents

In order to reduce data analysis errors, pre-processing such as unifying uppercase letters of IPC information and removing blanks, “-”, “/” was performed.

		Section (A ~ H)	Class	Sub class	Main Group	Sub Group
Total Number		8	131	647	7,545	70,191
Example (G05D1/02)	Symbol	G	05	D	1	02
	Title	PHYSICS	CONTROLLING; REGULATING	SYSTEMS FOR CONTROLLING OR REGULATING NON-ELECTRIC VARIABLE	Control of position, course or altitude of land, water, air, or space vehicles, e.g. automatic pilot	Control of position or course in two dimensions

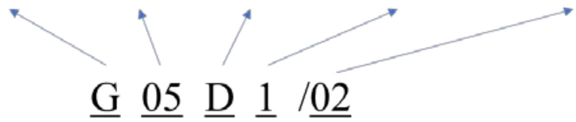

Fig. 4. Example of IPC hierarchy and information and total number of IPC

The goal of the IPC is the classification which is a means for obtaining and uniform classification of patents internationally. Moreover, the classification has important purposes; a search tool of patent for the orderly arrangement to facilitate access to information of technology and investigating cutting-edge technology in given area [43-44]. IPC consists of the hierarchy of section, class, subclass, main group, and sub group. Each section is designated by one of the capital letters A through H. Each section is subdivided into classes which are the second hierarchical level of the classification and also main group and sub group. Each section, class, subclass, main group, and sub group has title, which provides technology information. As shown in **Fig. 4**, for example, G05D1/02 technically means the control of position or course in two dimensions (sub group) of control of position, course or altitude of land, water, air, or space vehicles, e.g. automatic pilot (main group) of systems for controlling or regulating non-electric variable (sub class) of controlling; regulating(class) of physics (section). For this study, patent information is used up to main group of IPC.

4.2 Evaluation

For LDA analysis, the number of topics must be determined. This can also be determined at a level where the researcher can effectively interpret the results. In this study, by changing the number of topics from 2 to 50 for the LDA function, the value at which the harmonic mean of the log-likelihood value becomes the maximum is determined by the number of topics [45]. As shown in **Fig. 5**, the optimal number of topics is 5 for P1, 7 for P2 and 5 for P3.

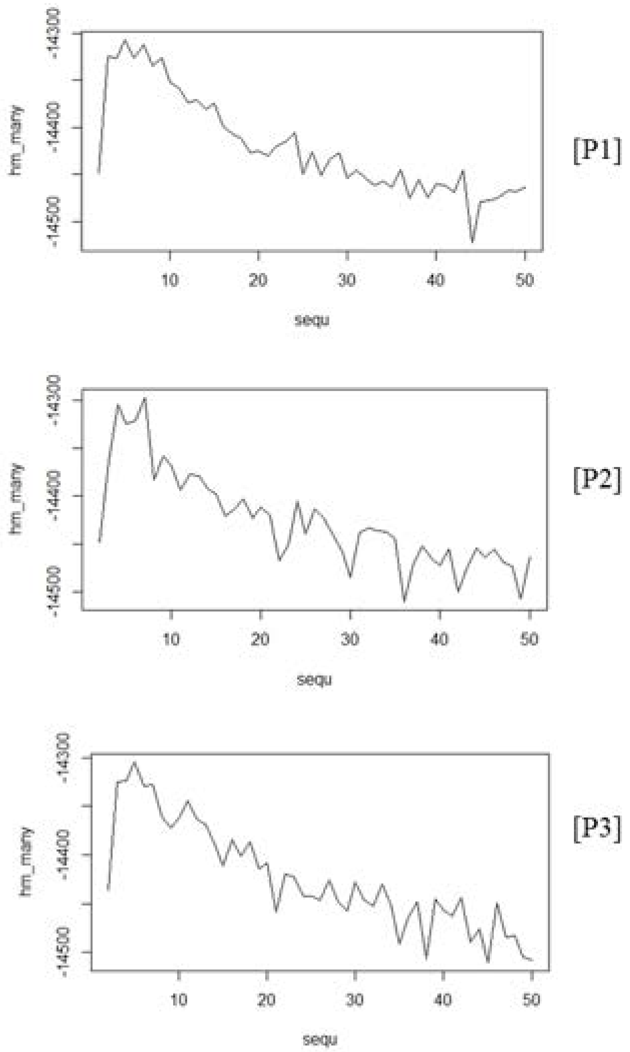

Fig. 5. The result of calculating optimal number of topics for P1, P2 and P3

4.3 LDA Analysis and results

As a result of the LDA analysis, the results shown in **Table 1** were derived for the top IPCs showing high frequency in each period of automotive semiconductor technology. The highest frequency IPCs were H04N05 in P1, G05D01 in P2, and G06K09 in P3. As the result, main automotive semiconductors of technologies are G06K09; methods or arrangements for recognizing patterns (main group) of graphical data reading (sub class) and G05D01.

Table 1. Main IPC analysis results of automotive semiconductor patents

No	P1 (Total 8,130 of IPC)		P2 (Total 34,409 of IPC)		P3 (Total 47,448 of IPC)	
	IPC	Frequency	IPC	Frequency	IPC	Frequency
1	H04N05	231	G05D01	1,568	G06K09	1,889
2	G06K09	221	G06K09	1,107	G05D01	1,729
3	G05D01	201	G08G01	981	G06N03	1,341
4	H04W04	174	H04W04	895	G06T07	1,308
5	G06F17	135	H04N05	862	H04W04	1,186

As shown in the **Table 2**, the number of patent documents included in each topic by period shows a similar distribution. Each topic can be considered to represent automotive semiconductor technology by period.

Table 2. Patent frequency and probability of topics in P1, P2 and P3

	P1		P2		P3	
	Patent Frequency	Probability	Patent Frequency	Probability	Patent Frequency	Probability
Topic1	367	22.9%	874	16.5%	1,678	21.9%
Topic2	340	21.2%	856	16.2%	1,282	16.8%
Topic3	318	19.8%	815	15.4%	1,638	21.4%
Topic4	297	18.5%	710	13.4%	1,392	18.2%
Topic5	284	17.7%	777	14.7%	1,656	21.7%
Topic6	-	-	610	11.5%	-	-
Topic7	-	-	645	12.2%	-	-
Total	1,606	100%	5,287	100%	7,646	100%

For the topics derived from P1 to P3, the most salient IPC constituting each topic was analyzed, and the patent documents constituting the topic were checked to find out the characteristics of each technology. The **Table 3** shows the IPCs and proportions that make up the topics by period.

Based on IPCs of registered patent documents from 2012 to 2020, we identified the automotive semiconductor technologies through patent analysis and LDA analysis. Automotive semiconductor technologies shown in this study are classified into 5 topics in P1, 7 topics in P2, and 5 topics in P3, and various core technologies can be identified. In P1, the main technologies are identified “General computing (P1T1; Period1 Topic1)”, “Sensing/traffic control (P1T2)”, “Graphical system (P1T3)”, “Driving Assistance/service (P1T4)”, “Communication network (P1T5)”. In P2, the main technologies are “Graphical system (P2T1)”, “Driving Assistance/service (P2T2)”, “Driving control for vehicles (P2T3)”, “Sensing system (P2T4)”, Driving control for road vehicles (P2T5)”, “Wireless Services (P2T6)” and “Communication network/Charging batteries (P2T7)”. In P3, the main technologies are “Sensor data processing (P3T1)”, “AI Service/Assistance (P3T2)”, “Imaging (P3T3)”, “Communication network (P3T4)”, and “Driving control (P3T5)”. In the case of

P2T3, the driving control technology of P2 was applied to various mobility such as vehicles, UAVs, drones, delivery and robots, etc., whereas in the case of P2T5, it was limited to road vehicles. In the case of P2T4, sensor technologies such as lidar, radar, image, and multi-view video are identified. P3T2 was analyzed as various service-related technologies such as biometrics, wireless, and commerce, and machine learning was applied in various ways. P3T5 was investigated as a driving control technology that combines both P2T3 and P2T3 application fields.

Table 3. Most salient IPC of each topic in each period

	P1		P2		P3	
	IPC	**Probability**	**IPC**	**Probability**	**IPC**	**Probability**
Topic1	G06Q10	4.0%	H04N05	18.1%	G01S17	11.9%
	G06N03	3.6%	H04N07	5.0%	G01S07	9.8%
	H02J07	3.5%	H04B10	3.5%	G06F11	6.4%
	B25J09	3.3%	G06F01	2.8%	G06F09	6.2%
	B60L11	3.1%	B60L11	2.5%	G06F21	5.8%
Topic2	G01S17	7.8%	G06F03	9.7%	G06N03	13.3%
	G01C21	7.3%	A61B05	7.8%	H04W04	11.7%
	G01S19	6.5%	G06F16	7.5%	H04L29	8.4%
	G08G01	5.8%	G06Q10	6.1%	G06Q10	4.5%
	H01L21	5.6%	G07C05	5.8%	G06N20	4.5%
Topic3	H04N05	13.7%	G05D01	32.4%	G06K09	19.6%
	G06K09	12.5%	B64C39	8.4%	G06T07	13.5%
	G06F17	8.0%	G06N03	6.0%	H04N05	11.9%
	H04B10	6.9%	G08G05	4.0%	G06F16	9.1%
	G06T07	6.0%	G01N33	2.3%	G06F03	7.0%
Topic4	G05D01	11.7%	G06K09	21.7%	H04L12	5.6%
	G06F03	6.4%	G01S17	14.0%	H01L27	3.8%
	H04N21	4.6%	G06T07	12.7%	H01L23	3.5%
	A61B05	3.9%	G01S07	9.4%	H04W72	3.3%
	G06F09	3.3%	G01S13	6.9%	H04B07	3.1%
Topic5	H04W04	9.7%	G08G01	19.3%	G05D01	17.8%
	H04L12	6.9%	G01C21	15.5%	G08G01	11.1%
	H04L29	6.2%	B60W30	11.1%	G01C21	6.7%
	H04W72	5.9%	B60W50	7.2%	B60W50	5.9%
	H04B07	4.3%	B60W10	6.2%	B60W30	5.8%
Topic6	-	-	H04W04	17.6%	-	-
			H04L29	12.4%		
			H04L12	7.2%		
			G01S19	5.9%		
			H04W12	4.7%		
Topic7	-	-	H04W72	6.6%	-	-
			B60L53	4.4%		
			H04W76	4.2%		
			H01L23	3.8%		
			H04B07	3.8%		

In this study, cosine similarity was measured to judge the similarity of topics from P1 to P3. Among the methods of measuring similarity between documents, cosine similarity measurement is widely used [46-48]. The cosine similarity expresses the degree of similarity between two feature vectors as a cosine value, and the cosine similarity has a value ranging from -1 to 1. -1 means they are completely opposite to each other, 0 means they are independent of each other, and 1 means they are completely equal to each other. In this study, the cosine similarity between topics in period was calculated using the top 30 IPCs of each topic. There are various studies on the threshold of cosine similarity [49-52], in this paper, we analyzed it in 4 steps; 0 ~ 0.1: independent, 0.45 ~ 0.49: slightly similar, 0.50 ~ 0.75: similar, 0.75 ~ 1.00: very similar. As a result of cosine similarity for each topic in P1, P2, and P3 shown in **Fig. 6**, it was analyzed that the technologies of each topic in P2 and P3 had low similarity and the classification by technology was relatively clear. On the other hand, the similarity of each topics in P1 was measured to be high, and even though they were classified into topics, it was investigated that the technology classification of automotive semiconductors was not clear. As the technological requirements and consumer demand for automotive semiconductors such as autonomous driving and AI service etc. were clearly identified, clear technical characteristics and application fields appeared from the P2 period.

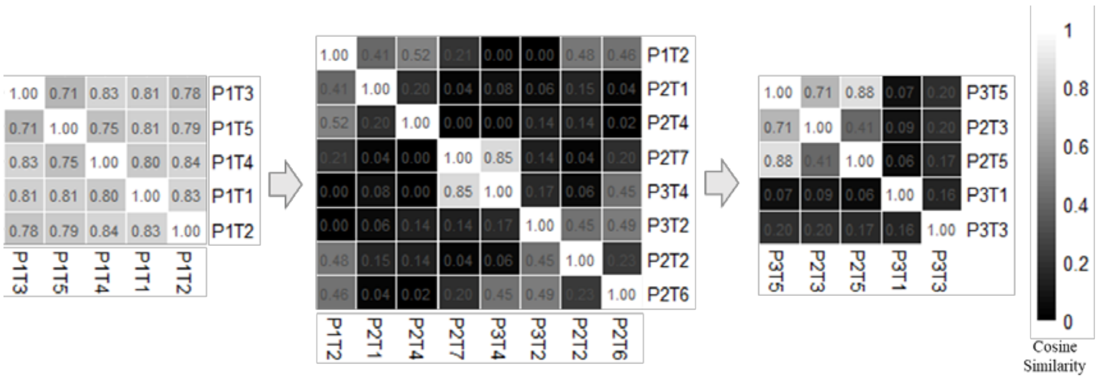

Fig. 6. Heatmap presentation of cosine similarity of topics in each period

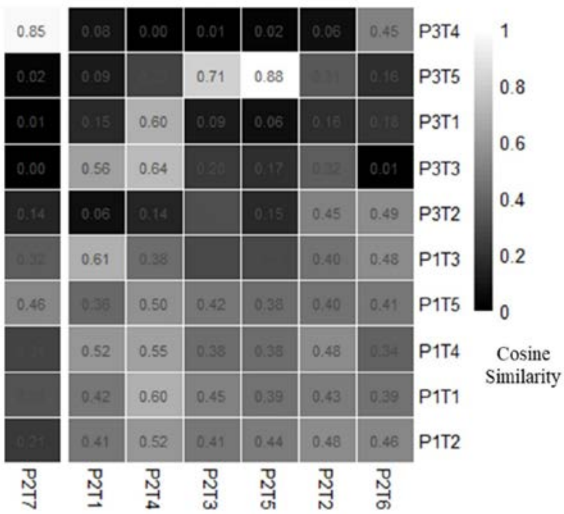

Fig. 7. Heatmap presentation of cosine similarity of topics b/w P1 and P2 and b/w P2 and P3

As shown in **Fig. 7**, it can be discovered that many of cosine similarities of automotive semiconductor technology are in the range of 0.4~0.6 when moving from P1 to P2. It can be seen that the technology of P1 affects the technology of P2 to a certain extent and the technology path is broadly connected. On the other hand, when moving from P2 to P3, it can be seen that the cosine similarity value significantly drops when a specific topic is excluded. It can be investigated that when moving from P2 to P3, technology classification becomes clear.

As shown in **Fig. 8**, the technology path was divided into emerging technology, slight emerging technology, convergence technology, slight convergence technology, similar technology, similar and convergence technology, and independent technology according to cosine similarity. The P2T3 and P2T5 technologies can be analyzed to be emerging technologies because no similarity of 0.5 or more was measured in P1. P2T2, P2T6, P2T7, and P3T2 technologies do not measure more than 0.5, but technologies with a similarity of 0.45 or more are calculated, so it can be analyzed as slight emerging technology.

On the other hand, P2T1, P2T4, P3T3, and P3T5 technologies can be considered convergence technology as they are influenced by more than 0.5 in two or more topics in the previous period. P2T2, P2T6, P3T2 and P3T4 technologies can be considered slight convergence technology as they are influenced by more than 0.45 in two or more topics in the previous period. Most similar technologies were P2T7 and P3T4, with the similarity of 0.883, showing that similar technologies are evolving. In particular, in the case of P3T5, it is greatly affected by both P2T3 (0.720) and P2T5 (0.883), and analyzed as similar technology and convergence technology. Many technologies with a similarity of 0.1 or less appeared in the technologies between P2 and P3, and were identified as independent technologies. On the other hand, there was no independent technology between P1 and P2.

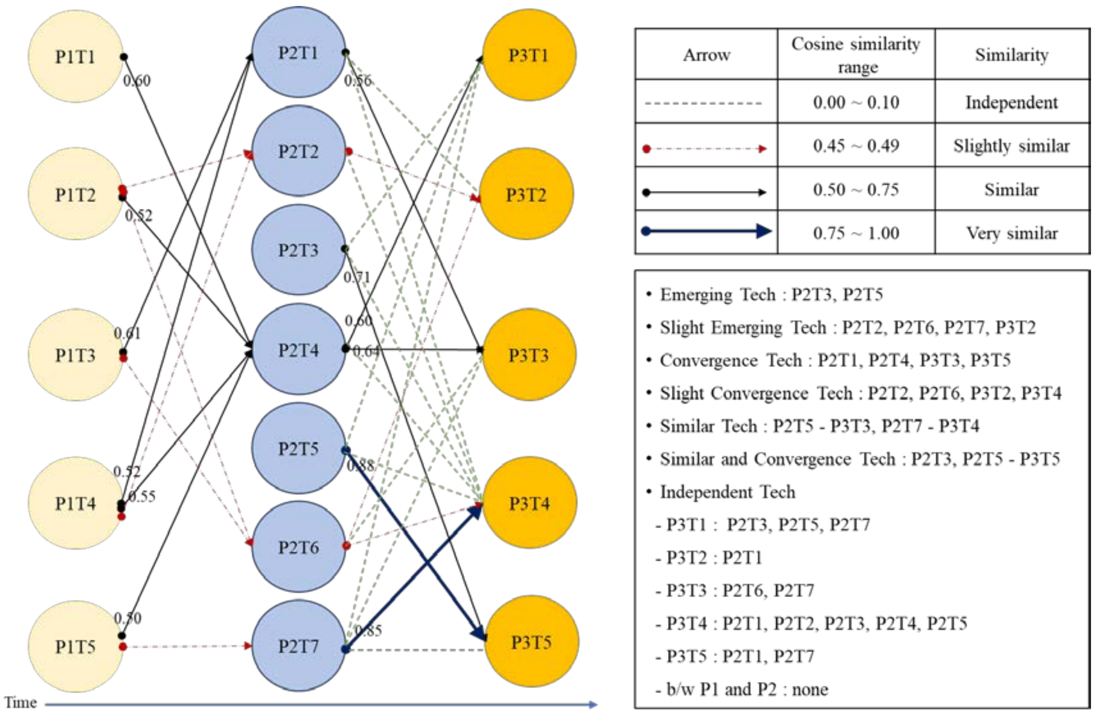

Fig. 8. Technology path through b/w P1 and P2 and b/w P2 and P3

5. Conclusion

This study analyzed the emerging and convergence of automotive semiconductor technologies with a patent-based topic modeling and cosine similarity. In the era of convergence, it is important to classify numerous technologies and to identify core technologies and technology trends. This study presented core technologies by period and technology trends through quantitative analysis using patent documents, which are aggregates of technological information. The technology trends derived from this study are expected to help in decision-making for R&D policy establishment in the automotive semiconductor industry and technology strategy establishment in the industry. In addition, it is expected to be effectively utilized in establishing detailed R&D directions and patent strategies by providing detailed core technology classification and trend analysis results.

The future research directions based on the results of this study are as follows. In this paper, due to the characteristics of the IPC hierarchy, the identification of core technology has a limitation in that both the application field and the functional aspect appear. Also, there is a limitation in identifying each topic as a dominant technology based on IPCs et al. In addition, although there are cited patents and family patents of patents that can confirm the connectivity between technologies, the application of the method using cosine similarity for this study has limitations and differentiation at the same time. Therefore, it is judged that more intuitive and readable research is possible if the number of topics increases, and the abstract of the patent, claims, or thesis are considered together. In this regard, it is expected that a study, adopting broader perspectives, on technology trends and business responses between companies in each country will be possible if analyzed by countries and applicants.

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