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A STUDY ON PREDICTIONS OF TECHNOLOGY CONVERGENCE IN DEFENSE TECHNOLOGIES

Kyung-Soo Kim[1] and Nam-Wook Cho[2,*]

[1]Technology Evaluation Center Organization
Worldwide Intellectual Property Service (WIPS) Co., Ltd.
189 Sungam-ro, Mapo-gu, Seoul 03929, Korea
ks@wips.co.kr

[2]Department of Industrial and Information Systems Engineering
Seoul National University of Science and Technology
232 Gongreung-ro, Nowon-gu, Seoul 01811, Korea
*Corresponding author: nwcho@seoultech.ac.kr

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Abstract. *This study aims to predict technology convergence in the defense field using link prediction. Based on the patents in South Korea, a link prediction model for convergence in military technology has been presented. The result shows that IT technologies are likely to play a crucial role in converging military technologies. In particular, measurement, control, and computing technologies are intermediaries, driving convergence across the present and future. While the importance of gunpowder and traditional weapon technologies will diminish, the importance of aircraft technologies such as drones will be greater. Furthermore, the network analysis shows that the convergence network will be more centralized and dense, which means that the convergence of technologies will strengthen in the future. This paper's main contribution is to present the future direction of defense R&D promotion from the viewpoint of technology convergence.*
Keywords: Technology convergence, Defense technology, Link prediction, Social network analysis

1. **Introduction.** Technology convergence is defined as the combination of at least two or more separate technology areas [1,2]. Technology convergence is one of the most efficient ways to innovate [3], providing technological breakthroughs [4]. As technologies become more connected, technology convergence becomes more critical. For the advancement of national defense, South Korea has been promoting technology convergence through various policies [5]. The Agency for Defense Development (ADD) has been leading South Korea's military R&D, cooperating with research institutes, universities, and defense industries.

While technology convergence has attracted significant interest in many areas, studies on technology convergence have focused on analyzing present convergence characteristics. Research on technology convergence includes the identification of convergence technology [6], pattern analysis [7,8], and characteristic analysis [9]. However, most previous studies are limited to analyzing the convergence phenomenon between technologies based on past data, and research to predict future convergence technologies is insufficient [10].

Patent information has been widely used as an index to analyze technology convergence [11,12]. In general, a patent's International Patent Classifications (IPCs) are defined as nodes, and the co-occurrence of IPCs is defined as a link, constituting convergence networks between technologies. Therefore, the prediction of a link that is likely to occur in a technology convergence network is key to the prediction of technology convergence.

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Recently, research on the prediction of convergence technology using link prediction has attracted interest in various fields [12-15]. Research on technology convergence using link prediction techniques has been primarily based on similarity-based approaches [16]. However, interest in link prediction based on machine learning has recently been increasing. Feng et al. [15] combined network analysis and link prediction to explore potential technology convergence relationships and topics in the electric vehicle industry. Cho et al. [16] used topic modeling and a link prediction method to predict patterns of technological convergence in chemical engineering and environmental technology. However, studies on link prediction in defense technologies have been limited.

This study aims to predict technology convergence in the defense field using link prediction. Machine learning algorithms, including Support Vector Machines (SVMs) and Random Forests (RFs), have been applied to the patents registered by ADD from 2010 to 2019. This study is meaningful in that it presents an extensive empirical analysis of technology convergence characteristics in Korea's military industry across time and in the technology areas. The rest of this paper is organized as follows. Section 2 provides the procedures and methodologies used in the paper. Section 3 explains the results of the link prediction and convergence analysis. Finally, Section 4 discusses the benefits and limitations of our research.

2. **Methods.**

2.1. **Data preprocessing.**

First, patent data in military technologies across ten years (2010-2019) applied by ADD were collected. A total of 5,109 patents were collected. Among the data collected, 3,410 patents had multiple IPCs, on which our research has conducted. To perform machine learning-based link prediction, we divided the data into three periods: training dataset (P1: 2010-2014; 1,490 patents), validation dataset (P2: 2015-2016; 756 patents), and test dataset (P3: 2017-2019; 1,164 patents).

The IPC code is one of the most popular and common ways to classify patents [19]. The IPC code consists of the section, class, sub-class, main group, and sub-group. In this study, network analysis has been conducted at the sub-class level.

The patent data for each period were converted into an IPC-IPC adjacency matrix. Convergence technology pairs and convergence technology pair candidates were identified by the similarity between IPCs. The average similarity value of convergence technology pairs was used as a cut-off value. It is assumed that the higher the similarity, the higher the probability that a link will occur. The similarity index, Jaccard similarity, Cosine similarity, and Pearson correlation coefficient were used as the features of machine learning algorithms.

In link prediction, a class imbalance is a common problem. In our training dataset, only 88 links (7.4%) among the 1,840 IPC pairs were identified. In this study, a SMOTE method was used to generate data with a small proportion. The SMOTE algorithm creates the artificial objects of the minority class based on the similarities in the feature space between the existing objects using the k-nearest neighbor algorithm [20,21]. As a result, the training dataset can be more balanced so that 53.8% of IPC pairs have links.

In this study, SVM and RF algorithms were used to train the link prediction model. SVMs attempt to identify the hyperplane that best represents the most significant separation between borderline data points, thereby commonly used for classification [22]. An RF algorithm is an ensemble learning method for classification, based on classification trees [23]. The advantages of RF include its ease of use and its robustness to overfitting [24,25]. In addition, RFs are known to be more appropriate for "large p, small n" problems [26].

As input variables of the model, the average value of similarity and centrality per each period were used. Jaccard similarity, Cosine similarity, and Pearson's correlation coefficient were used as the similarity indices. For centrality indicators, degree centrality, closeness centrality, and betweenness centrality were used. As the target variable of the model, the presence or absence of link occurrence in the next period was used.

2.2. **Technology convergence analysis model.** The characteristics of convergence were defined by utilizing the role model of convergence. As shown in Figure 1, suppose the top 10 technologies with degree centrality are defined as set A, and the top 10 technologies with betweenness centrality are defined as set B. The intersection of A and B^C is defined as the convergence group, leading to the convergence between technologies. The intersection of A^C and B is defined as the intermediation group, a broker in technology convergence. The intersection of A and B is defined as the convergence and intermediation group.

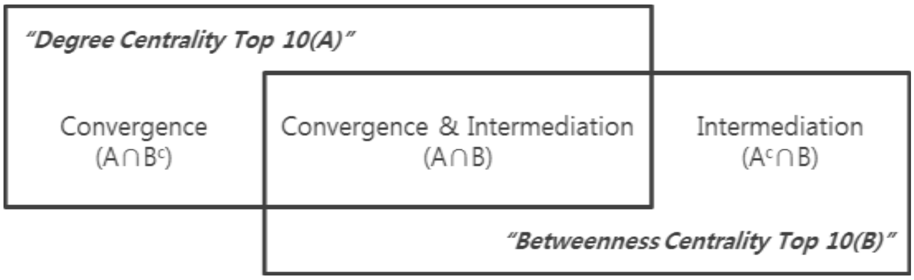

Figure 1. Technology convergence analysis model

3. Results.

3.1. **Link prediction.** The link prediction model was trained using the training dataset (P1: 2010-2014), and the prediction model was evaluated using the validation dataset (P2: 2015-2016). Accuracy, sensitivity, and specificity indicators were used to evaluate the predictive model's performance. In the case of unbalanced data, the sensitivity can be used as an evaluation measure [27-29]. As shown in Table 1, RF showed better accuracy and specificity, while SVM showed better sensitivity. Then, the link prediction model has been applied to the test data set (P3: 2017-2019) to predict future convergence technologies. 548 links were predicted through SVM, and 232 links were predicted through RF. The number of commonly predicted links is 212, upon which our convergence analysis has been performed.

Table 1. Result of performance evaluation

Measures	Performance evaluation		
	Formula	SVM	RF
Accuracy	TP + TN/TP + TN + FP + FN	0.726	0.880
Sensitivity	TP/TP + FN	0.632	0.289
Specificity	TN/TN + FP	0.733	0.922

TP: True Positive; TN: True Negative; FP: False Positive; FN: False Negative

3.2. **Characteristics of convergence.** Based on the results of a link prediction model, convergence characteristics of future military technologies have been analyzed by using Social Network Analysis (SNA). Data processing, launching apparatus, and aircraft technology are identified as the central convergence technologies in the future, while blasting, electrical measurements, and image data processing technology are predicted to be intermediary technologies. Measurement, control, calculation, and aircraft technologies are central and intermediary technologies for future convergence in the military.

The percentage of measurement, control, and computation technologies (G01, G05, G06) is predicted to increase from 46.2% to 57.1%. Explosives (C06, C08), lifesaving (A62), and textile treatment (D06) technologies account for 30.8%; they are likely to diminish in the future. Although the convergence of aircraft (B64) technologies does not exist, it is predicted to account for 21.4% in the future.

Figure 2 presents future convergence networks. The future convergence network exhibits a more significant component, illustrating that the concentration and the density index value increased significantly. The result shows that IT technologies will play a crucial role in the convergence of military technologies. In particular, measurement, control, and computing technologies are intermediaries, driving convergence across the present and future.

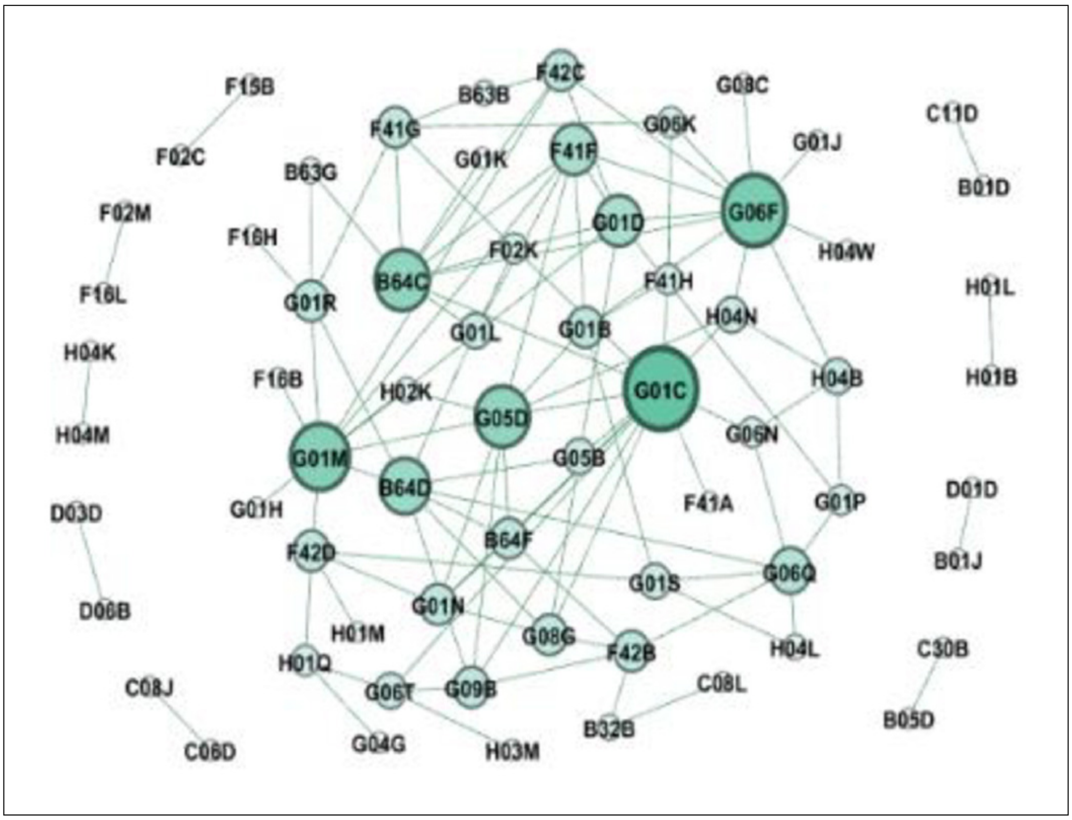

Figure 2. Future technology convergence network

4. **Conclusions.** The main contribution of this paper is to show the future direction of defense R&D promotion from the viewpoint of technology convergence. As a technology strategically promoted by the government, it can be interpreted that investment centered on applied research is necessary to graft it into a mature technology. The results can be used as primary data for judging priorities between sectors when the government establishes investment strategies in the defense sector.

Although ADD plays a representative and crucial role in military R&D in South Korea, the patents of ADD cannot represent the R&D of the whole country. Thus, extending the data collection and providing further analysis would be a suitable future research topic. In addition, it would be meaningful also to employ features more specific to the military industry, which would enhance the performance of our link prediction model.

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