Classification of Radar Signals with Convolutional Neural Networks

Seok-Jun Hong*, Yearn-Gui Yi*, Jeil Jo**, Bo-Seok Seo*
* Dept. of Electronics Engineering, Chungbuk National University, Cheongju, Korea
** Agency for Defense Development, Daejeon, Korea

Abstract - In this paper, we propose a method to classify radar signals according to the jamming techniques by applying the machine learning to the parameter data extracted from the received radar signals. In the present army, the radar signal is classified according to the type of threats by referring to the library composed of radar signal parameters mostly built by prior investigations. Since radar technology is continuously evolving and diversifying, however, the library based method can not properly classify the signals for new threats which are not in the existing libraries, thus limiting the choice of appropriate jamming techniques. Therefore, it is necessary to classify the signals so that the optimal jamming technique can be selected by using only the parameter data of the radar signal. In this paper, we propose a method based on machine learning to cope with new threat signals of radars. The method classifies the radar signals according to the jamming method with convolutional neural networks, and does not refer to the preexisting library.

***Keywords* - radar signal classification, jamming technique, machine learning, convolutional neural networks**

I. Introduction

The purpose of jamming is to prevent the enemy from freely using radio waves in electronic warfare environment. Jamming techniques can be classified into communication jamming and radar jamming. The primary difference between radar and communication jamming is in the geometry. Whereas a typical radar has both the transmitter and the associated receiver at the same location, a communication link always has its receiver in a different location from that of the transmitter [1]. Communication is generally done using transceivers which have a transmitter and a receiver together. Therefore, for communication jamming, we need to interfere both equipments locating at different places if necessary.

Radar jamming defends against enemy attacks by disabling search and/or tracking of enemy radars, and prevents missile or guided missile attacks on aircraft, ships or ground vehicles [2].

Conventionally, to apply the jamming technique against the enemy radar, threat radar signals are first collected and analyzed over a long period of time, and the signals are classified according to the parameters of the signals. Radio frequency (RF), pulse repetition interval (PRI), pulse width, etc. are used as radar signal parameters. Then select an appropriate jamming technique according to the parameters classified [3]. The mapping relationship between the parameters of the radar signal and the jamming technique to disrupt that radar signal is summarized in a library.

The conventional library based method has a limitation in assigning an appropriate jamming technique to a new threat or new type of threat that do not exist in the existing library. Therefore, a new classification method is required to specify the proper jamming technique for unknown or new radar signals.

In this paper, we propose a method to adaptively classify radar signals into corresponding optimal jamming techniques without a library. The method uses machine learning by using the parameters of the threat radar signal as inputs. The convolutional neural networks are used for the classifier and learned using the existing library. Simulation results show that the proposed method can classify unknown or new types of threat radar signals which can not be classified by the library based methods.

II. How To Classify Radar Signals?

In this paper, we consider only pulse radars which occupy most of the radars used in modern warfare. Fig. 1 shows the signal shape of a typical pulse radar. Radio frequency (RF) signal is modulated by a pulse and the RF pulse is repeated at regular or irregular intervals called pulse repetition intervals (PRIs). Parameters for the radar signals include RF, PRI, pulse amplitude (PA), pulse width (PW), and so on.

Conventional signal classification for selecting an appropriate jamming method is performed in three steps: signal analysis, radar parameter type determination, and parameter-type-to-jamming-method-mapping by library as shown in Fig. 2 [3]. The signal analysis is to extract the parameters for each pulse of the radar signal. In general, since the receiver simultaneously receives multiple signals from multiple radars, so that each radar signal should be distinguished in the analysis process. A parameter vector called a pulse description word (PDW) is then estimated for each pulse of each radar signal. As

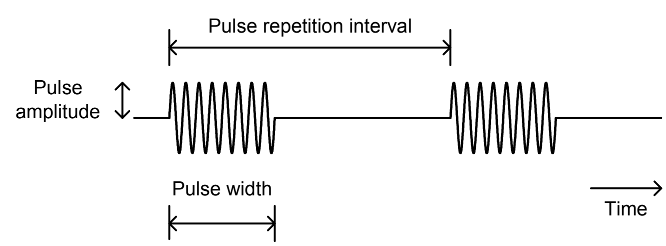

Fig. 1. Typical radar pulses

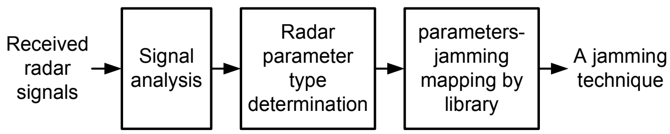

Fig. 2. Structure of the conventional radar signal classification method

mentioned above, the elements of the PDW include the center RF of the modulated pulse, PRI, PA, PW, and so on [2].

In the parameter type determination step, a change form of each parameter is estimated from a predetermined number of PDWs. Fig. 3 illustrates the eight variation types of PRI: stable (or fixed), jitter (or agile), stagger (or hopping), dwell and switch (or multi-level hopping), sine, sawtooth+, sawtooth-, and triangle patterns [3].

At the final step, by referring to the existing library, an appropriate jamming technique corresponding to the type of change in the radar signal parameters is obtained. The library is constructed on empirical results by collecting, analyzing, and accumulating PDW data over a long period of time. For given radar signal parameters, selecting a jamming technique is equivalent to classifying the parameters into a class to which the jamming method belongs.

III. The Proposed Classifier

Extracting parameter vectors or PDW data from the received radar signal requires very complicated signal analysis [3], and is a separate area from the parameter classification for selecting the jamming method. In this paper, therefore, we consider a method of classifying radar signal parameters which are assumed to be completely extracted.

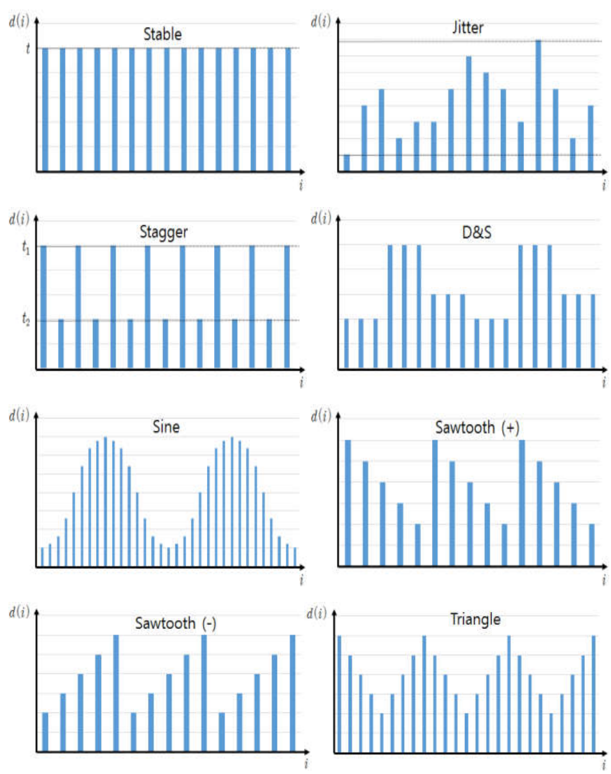

Fig. 3. Variation types of pulse repetition interval over time

A. Convolutional neural network for a classifier

The convolutional neural network (CNN) of [5] is used for parameter classification. The CNN is a powerful technology for classification of image inputs [4]. It reveals excellent results on several benchmarks with very simple data [5]. In addition, it is an effective model to classify not only color images but also black and white images [6].

Two most important characteristics of radar signals, RF and PRI of the pulse and their corresponding jamming technique, are used as the learning and test data. We consider the eight PRI changes shown in Fig. 3 and seven types of RF except for the stagger pattern.

B. Machine learning to classify radar parameters

The proposed system for classifying radar parameters of RF and PRI into the class to which a jamming technique belongs is shown in Fig. 4. First, a $2 \times N$ matrix, where N is the number of each parameter, is converted to a $40 \times N/20$ matrix or an image. The values of the image are normalized to a minimum value of 0 and a maximum value of 1.The CNN is learned by this image to be classified into the specific class where the radar jamming technique belongs.

Fig. 5 shows an example of the images. The white part of the image shows a fixed form with no change in time, and the data with time variation shows some patterns.

C. Simulation Results

Simulation is divided into learning and evaluation processes. The number of RF and PRI parameter vectors or PDWs for each radar is 1000. And the number of radars to classify is 600 or 7000. Among them, 80% is randomly used for learning, and the remaining 20% is used to evaluate the performance of the classifier. To learn the CNN, 200 iterations performed. In this paper, there are four jamming techniques, and only one jamming technique is associated with each radar.

Fig. 6 shows the probability of successful classification and absolute error for the case of 600 radars. The figure shows that the probability of success is about 90% after 30 iterations and remains almost the same after that. It reaches about 93% after 200 iterations.

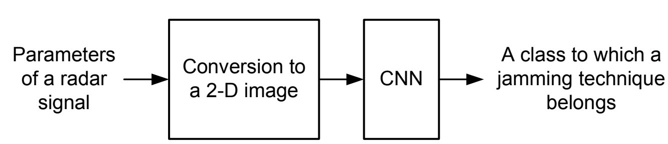

Fig. 4. The structure of the proposed classifier using CNN

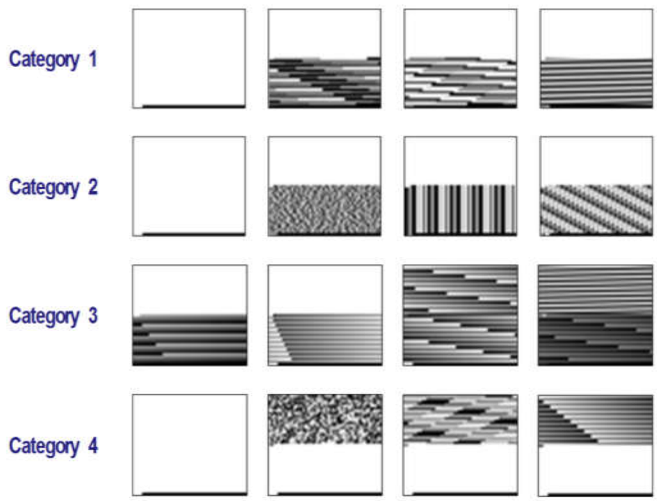

Fig. 5. Image of the 2-dimensional parameters of RF and PRI

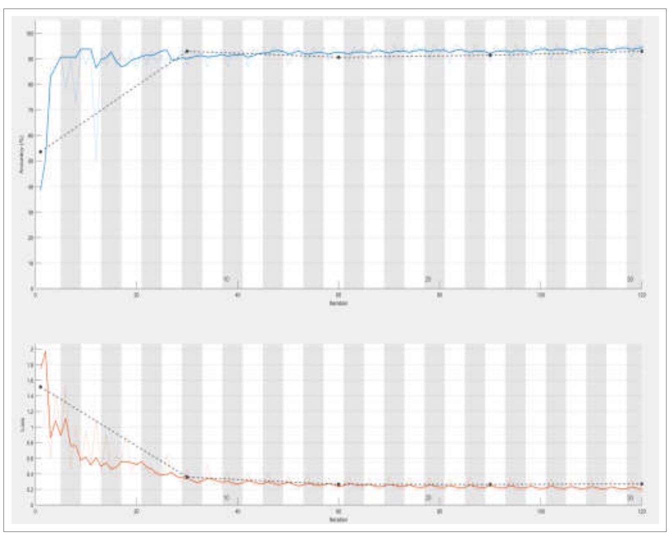

Fig. 6. Simulation results with 600 radars

Fig. 7 shows the experimental results with 7000 radars and 700 iterations. All conditions are the same except for the number of radars. In this case, the number of iterations that kept constant is 30, similar to the previous case. However, the probability of success is about 94% after 30 iterations, 97% after 200 iterations, and 98% after 700 iterations. Due to the nature of CNN, there are many iterations when there are many learning data.

As the amount of data used in the learning process increases, the probability of success in signal classification increases. From the analysis of the cases where the errors occurred, the dynamic range of the input values was large when the classification is failed. In addition, some errors occur because the distinction of the absolute values of the maximum, minimum, and interval is lost during the normalization process.

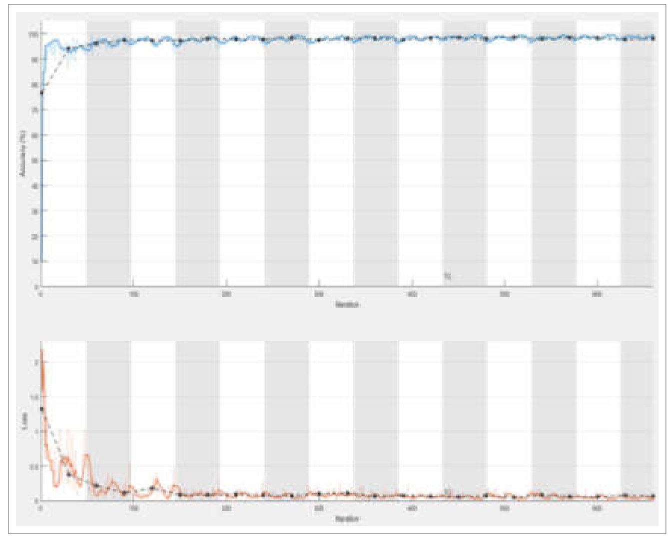

Fig. 6. Simulation results with 7000 radars

IV. Conclusions

In this paper, we propose an adaptive jamming selection method using CNN to overcome the limitations of the conventional library-based method which cannot solve for unknown or new radars. As the input for the machine learning, two radar signal parameters, carrier radio frequency and pulse repetition interval are used, which are important characteristics of the radar signals.

Simulation results show that the classifier works well for the new radar types which have not been learned previously. The error rate decreases as the number of learning radars increases, and is about 2% for 7000 radars.

Acknowledgment

This work has been supported by the Agency for Defence Development of Korea.

References

[1] David L. Adamy, *A Second Course in Electronic Warfare*, Artech House, 2004.

[2] Sergei A. Vakin, Lev N. Shustov, Robert H. Dunwell, *Fundamentals of Electronic Warfare*, Artech House, 2001.

[3] Richard G. Wiley, *ELINT: The Interception and Analysis of Radar Signals*, Artech House, 2006.

[4] Patrice Y. Simard, Dave Steinkraus, John C. Platt, "Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis," Proceedings of the Seventh International Conference on Document Analysis and Recognition, vol. 2, pp. 958–962, 2003.

[5] Yoon Kim, "Convolutional neural networks for sentence classification," Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pp. 1746-1751, 2014.

[6] Behnke Sven. *Hierarchical neural networks for image interpretation*, PhD thesis of Freie Universitat Berlin, 2003.