Performance Analysis of Radar Scan Pattern Classification using Visibility Graph

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***Abstract*—Accurate radar scan pattern classification is essential for identifying and responding to threats in electronic warfare systems. In this paper, we present an approach to enhance classification accuracy by leveraging visibility graphs to extract critical features from radar signals and applying the GoogLeNet deep neural network. By transforming radar scan patterns into visibility graphs, the method captures both global and local characteristics that are crucial for distinguishing between similar patterns. Simulation results demonstrate that the proposed approach achieves over 92% in terms of accuracy, precision, and recall, highlighting its effectiveness in radar scan pattern classification.**

***Index Terms*—electronic warfare systems, radar scan pattern, visibility graph**

I. Introduction

Electronic warfare (EW) encompasses all military applications that use electromagnetic waves to control or attack enemy systems. It consists of three components: electronic support (ES), electronic attack (EA), and electronic protection (EP) [1, 2]. Among these, ES is responsible for detecting and analyzing enemy signals, providing processed information that offers significant tactical advantages. However, traditional radar identification methods, which rely on basic parameters such as frequency, pulse width, and pulse repetition interval, face challenges in the complex signal environments of modern warfare [3-5]. To address these challenges, recent research focuses on leveraging radar scan pattern to enhance classification performance, enabling more accurate identification of radar types and operational states [6-11]. Radar scan patterns, such as circular, sector, helical, raster, and conical scans, offer vital clues about the nature and intent of enemy radar systems. Accurately recognizing and classifying these patterns is essential for predicting enemy movements and devising effective countermeasures.

We focus on enhancing radar scan pattern classification by modeling radar signals and converting them into visibility graphs [8]. These graphs capture the structural and dynamic characteristics of radar signals, facilitating the distinction between different scan patterns. The approach in [8] utilizes visibility graphs for recognizing radar antenna scan patterns. It employs traditional machine-learning techniques such as SVM to classify the visibility graphs derived from scan patterns. In this paper, we leverage the advanced capabilities of the inception modules within GoogLeNet [9], which are particularly adept at processing complex and multi-scale patterns. By combining visibility graphs with a deep learning model, we aim to improve classification accuracy, especially in challenging environments with low signal-to-noise ratios or similar radar patterns.

This paper is organized as follows: In Section II, we explain visibility graphs and introduce the GoogLeNet architecture. Section III presents the simulation setup and results, demonstrating the effectiveness of the proposed approach. Finally, we conclude the paper in Section IV.

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II. Methodology

In modern electronic warfare, accurate modeling of radar signals according to their scan patterns is significant for effective classification and analysis. According to [7], radar signals can be characterized by various scan patterns such as circular, sector, helical, raster, and conical scans. These patterns not only dictate the operational behavior of the radar but also affect the characteristics of the signals received by the electronic support (ES) system. By understanding these patterns, radar signals can be modeled more accurately, and this information can be used to improve identification techniques.

In this paper, we modeled the radar signals according to the methodology presented in [7]. This modeling method involves considering various operational parameters such as signal strength, pulse repetition interval, and environmental factors. The modeled radar signals are then converted into visibility graphs, which capture the essential structural features of the signals under various environments. Finally, we apply GoogLeNet to classify the scan patterns effectively.

A. Visibility Graphs Extraction [8]

Visibility graphs transform time-series data into a network, where each data point is a node, and edges are formed if there is visibility between them. This method effectively captures both local and global characteristics of radar signals, making it particularly useful for distinguishing between different scan patterns. This visibility is determined by whether a straight line can be drawn between two points without being blocked

Instant	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
2	1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0
3	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
4	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0
5	1	1	0	1	0	1	1	1	1	0	0	0	0	0	0	0
6	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0
7	0	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0
8	0	0	0	0	1	1	1	0	1	0	0	0	0	0	0	0
9	0	0	0	0	1	0	0	1	0	1	1	1	1	0	0	0
10	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0
11	0	0	0	0	0	0	0	0	1	1	0	1	0	0	0	0
12	0	0	0	0	0	0	0	0	1	1	1	0	1	0	0	0
13	0	0	0	0	0	0	0	0	1	0	0	1	0	1	1	1
14	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1
15	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1
16	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0

Fig. 1. The degree distribution matrix of visibility graph [8].

by any intermediate points.

When converting a time series into a visibility graph, we can define a degree distribution matrix, which is the number of connections between nodes in the visibility graph. If there is a connection between two nodes, the column and row corresponding to each node in the visibility graph matrix have a value of 1; otherwise, they have a value of 0. An example of a visibility graph matrix constructed according to this rule can be seen in Fig. 1. This matrix serves as the feature set for classification, capturing the unique characteristics of each radar scan pattern. The computational complexity of generating a visibility graph is generally $O(N^2)$, where N represents the number of data points in the radar signal. This complexity arises from the need to compare each node with every other node to establish visibility.

Fig. 2 illustrates the visibility graphs constructed for various radar scan patterns. These graphs reveal both similarities and differences among the patterns, highlighting how the structural features of radar signals manifest in the graph form. Both the circular and helical scan patterns, due to their continuous rotational movements, share a key structural similarity-they produce periodic graphs. The helical scan, while showing slight variations in pattern size as elevation increases, maintains the overall symmetry observed in the circular scan. Sector and raster scan patterns also exhibit similarities in their visibility graphs, as both involve restricted scanning ranges. The sector scan generates smaller, repetitive structures, while the raster scan adds stepwise changes in elevation, leading to a more complex yet similarly clustered graph. On the other hand, the conical scan pattern is distinct, with a visibility graph characterized by sinusoidal and cyclic structures. Its unique oscillatory nature sets it apart from the other patterns, making it easily identifiable.

This approach preserves both the local details and the global structure of the radar signal, making it a practical and adaptable tool for capturing the unique characteristics of different radar scan patterns. By reflecting both global and local patterns in the time-series data, visibility graphs enable

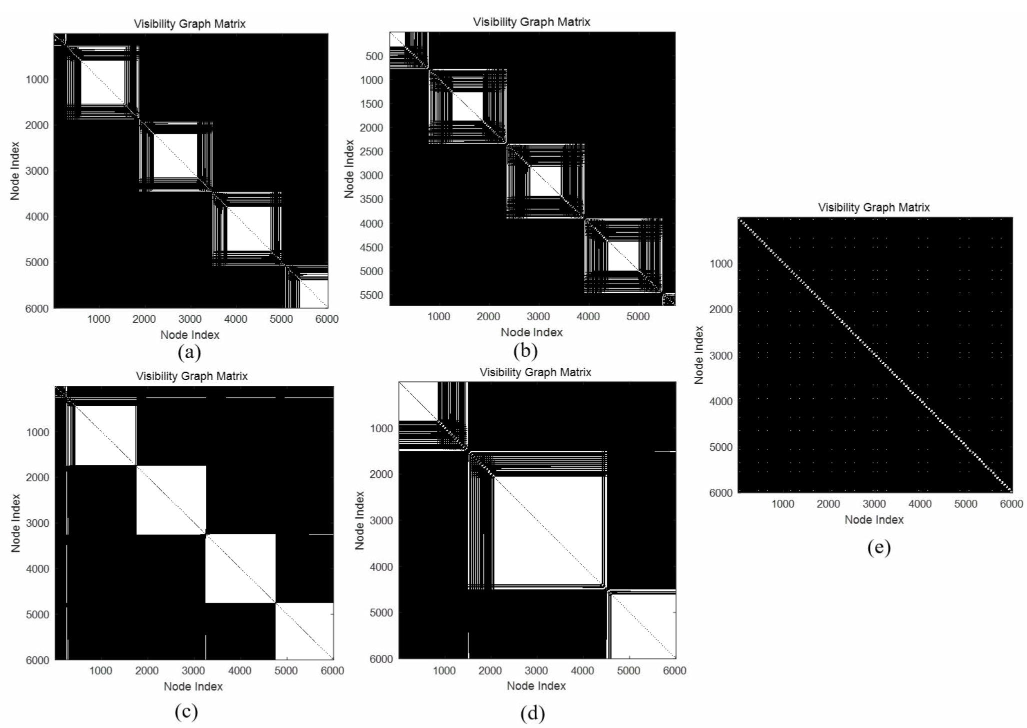

Fig. 2. Visibility graph of radar scan pattern received signal - (a) circular scan, (b) sector scan, (c) 4-bar helical scan, (d) 4-bar raster scan, (e) conical scan.

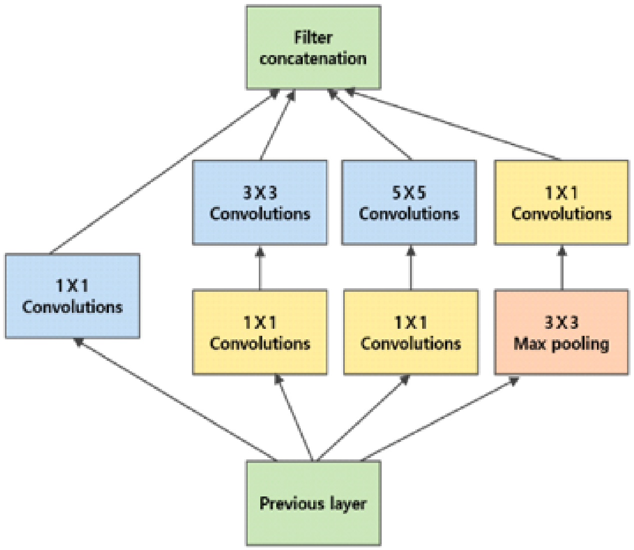

Fig. 3. Inception module model of GoogLeNet [9]

precise analysis of the dynamic changes in radar signals. In this paper, the visibility graphs derived from the received radar signals are used as input data for deep learning algorithms to classify the different types of radar scan patterns effectively.

B. GoogLeNet Deep Learning Algorithm [9]

GoogLeNet is a deep learning architecture that gained significant attention after winning the ILSVRC 2014 competition. It is comprised of 22 layers and is designed to improve neural network depth and width. The most distinctive feature of GoogLeNet is the introduction of the Inception module, which is depicted in Fig. 3. The Inception module allows for simultaneous processing of features at multiple scales by applying different convolution filters (e.g., 1x1, 3x3, 5x5) in parallel. This module enables the model to capture fine-grained details as well as broader patterns in the input data. To manage computational costs, 1x1 convolutions reduce the dimensionality before applying larger filters, making the network more efficient. Additionally, GoogLeNet employs Global Average Pooling (GAP) instead of fully connected layers towards the end of the network. GAP reduces the number of parameters significantly, contributing to the model's efficiency while maintaining high accuracy. To address the vanishing gradient problem that often occurs in deep networks, GoogLeNet incorporates auxiliary classifiers at intermediate layers during training, which provide additional gradients to earlier layers, ensuring effective learning.

Within each group, further classification is performed using the degree distribution matrices obtained from the visibility graphs. A decision tree is constructed to classify the signals into specific radar scan types, such as circular, sector, and helical scans.

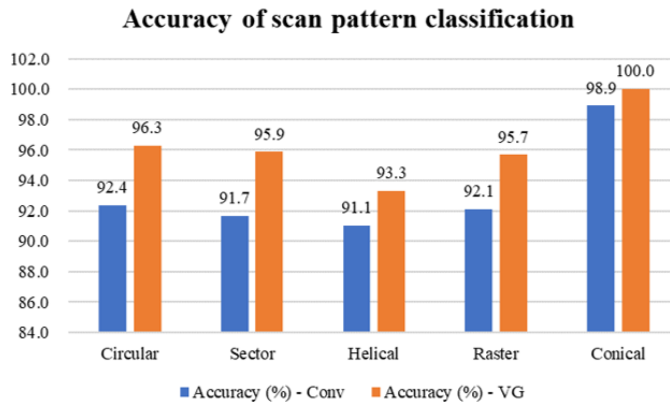

Fig. 4. Comparison of scan pattern classification accuracy using GoogLeNet.

III. Results

In this section, we evaluate the performance of the radar scan pattern classification using the GoogLeNet algorithm, as described in Section 2.2. The classification performance is compared using two feature extraction methods: the traditional method, spectrogram [7], and the visibility graph proposed in this paper. The spectrogram is a widely used technique that transforms radar signals into a time-frequency representation, capturing both the temporal and spectral characteristics of the signal. While effective in many applications, spectrograms may struggle with subtle variations in radar scan patterns, especially in low-SNR environments. In contrast, the visibility graph method preserves both local and global structures of the radar signal, offering a different perspective for classification.

For the simulation, radar signals corresponding to five different scan patterns—circular, bi-directional sector, helical, raster, and conical—were generated. Each pattern was simulated with various operational parameters to create 200 signals per pattern. From the total dataset, 80% was used for training, and the remaining 20% was reserved for testing.

We evaluated the algorithms using three metrics: accuracy, precision, and recall. Accuracy measures overall correctness, precision indicates reliability in positive predictions, and recall assesses the model's ability to capture relevant instances. These metrics provide a comprehensive evaluation of classification performance.

We compare the classification performance of two methods for radar signals with five different scan patterns: the traditional method that uses spectrograms as input to the GoogLeNet algorithm and the proposed method that utilizes visibility graphs as input to the same GoogLeNet algorithm. Figures 4-6 illustrate these comparisons, where the blue graph represents the performance of the traditional method, and the orange graph indicates the performance of the visibility graph-based method. The traditional method using spectrograms achieves an average accuracy of 93.2%, with a precision of 83.1% and a recall of 83.02%. In contrast, the proposed method using visibility graphs with the GoogLeNet model demonstrates an average classification accuracy of 96.2%,

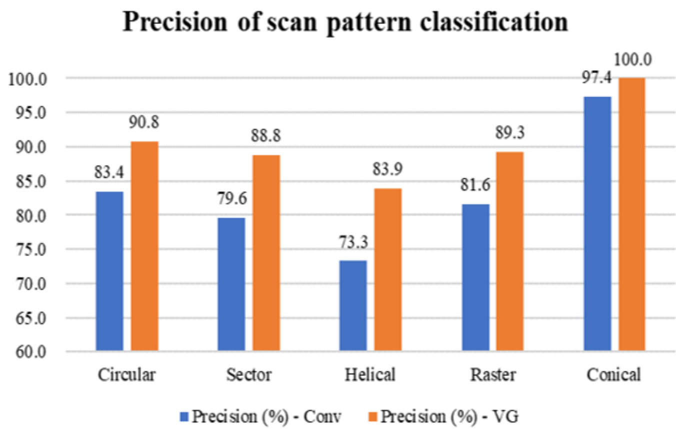

Fig. 5. Comparison of scan pattern classification precision using GoogLeNet.

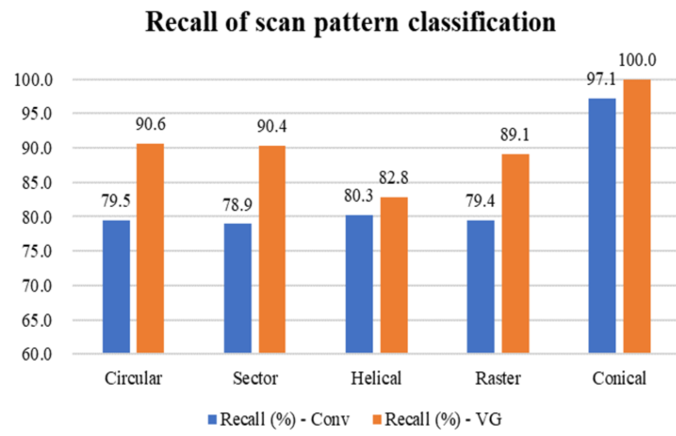

Fig. 6. Comparison of scan pattern classification recall using GoogLeNet.

with a precision of 90.6%, indicating that this deep learning algorithm is reliable. Furthermore, the recall rate of 90.6% on average highlights the superior performance of the proposed method. Overall, the visibility graph-based approach outperforms the traditional method across all three metrics. Additionally, the classification performance is observed to be highest for conical, followed by circular, sector, raster, and helical scans.

Traditional techniques for classifying radar scan patterns generally achieve around 80% classification accuracy on average [7,10-12] and often struggle to maintain consistent performance in environments with low SNR or high similarity between scan patterns. Although the application of deep learning algorithms has improved the classification performance of the spectrogram method, spectrograms have a drawback of high computational costs due to time-frequency resolution. The proposed method, which uses visibility graphs that can be expressed in binary (0 and 1) values, reduces computational complexity and achieves superior classification performance. This advantage makes the visibility graph-based method an effective and practical approach for radar scan pattern classification.

IV. Conclusion

We presented a method that applies a deep learning algorithm utilizing visibility graphs extracted from radar signals with scan pattern information to address radar identification challenges in ES systems. The simulation results demonstrated that the proposed approach, leveraging the GoogLeNet deep learning algorithm, outperforms traditional classification methods, achieving superior performance with accuracy, precision, and recall rates averaging above 92.5%. Future work will focus on enhancing classification accuracy by extracting additional feature vectors from visibility graphs and exploring various deep learning-based image classification models for performance comparison and analysis. These results support the development of improved radar signal analysis algorithms, helping electronic warfare systems handle complex threats. By enhancing classification accuracy and reducing computational complexity, our method offers an effective solution for radar signal analysis.

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