Classification of ISAR Images Generated from Model-based Approaches Using Deep Learning

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***Abstract*—The classification of small, low-observable airborne targets, such as drones and birds, poses significant challenges due to their low detection rates. Conventional vision sensor-based approaches often suffer from reduced performance in low-visibility environments or adverse weather conditions. Additionally, the integration of infrared sensors alongside camera sensors increases hardware complexity and cost, rendering such solutions inefficient. To address these limitations, we propose a method that leverages deep learning and inverse synthetic aperture radar (ISAR) imaging for accurate target classification, using only radar sensors. Our proposed deep learning-based ISAR image classifier comprises two key components: simulated ISAR image generation and deep learning-based classification. We construct simulated ISAR datasets using point scatter (PS) modeling for quadcopter drones, hexacopter drones, and aircraft, and three-dimension (3D) mesh modeling for birds, unmanned aerial vehicles, and quadcopter drones. The two datasets based on PS and 3D mesh modeling are used to train a proposed deep learning classifier. The proposed classifier can achieve a classification accuracy of 98% on the PS-based dataset and 96% on the 3D mesh-based dataset, where scattering was calculated using the physical optics method.**

***Index Terms*—deep learning, image classification, inverse synthetic aperture radar (ISAR), physical optics method, point scatter (PS) model, three-dimension (3D) mesh model**

I. Introduction

The rapid advancement of low-observable airborne targets, such as drones, has heightened the importance of accurate identification and classification techniques [1], [2]. Extensive research has been conducted to address this challenge, employing various types of sensors. For example, studies at [3], [4] focused on drone or stealth target identification using camera-based systems, while [5], [6] explored detection using radar sensors. However, vision sensors such as cameras face inherent limitations in poor visibility conditions, such as nighttime or adverse weather, hindering accurate identification. Consequently, radar systems have gained widespread adoption for identifying low-observable airborne targets.

In general, ground-based radar systems have been employed for drone identification through micro-Doppler analysis [7]. Nonetheless, a major limitation of micro-Doppler identification is its inability to determine the specific type of the detected target. This makes it difficult to distinguish between different types of drones or between drones and birds, especially in scenarios where precise classification is required. Recent research efforts have focused on leveraging inverse synthetic aperture radar (ISAR) systems for target identification and classification [8]–[10]. The ISAR image shows the two-dimensional distribution of high energy scattering centers of a target. Despite the potential of ISAR imaging for precise target classification, the challenge of acquiring adequate datasets remains a significant hurdle in remote sensing applications. Acquiring the ISAR images of airborne targets through real flight test is not only time-consuming but also cost ineffective. This problem is compounded when considering birds due to their unpredictable behavior and lack of controllability, which complicate data collection efforts. As a result, simulations have emerged as a practical solution, providing a controlled and cost-effective means to generate the necessary datasets for the classification of drones and birds using ISAR imagery. This approach offers the flexibility to model a wide range of target behaviors and environmental conditions, enabling the creation of large, labeled datasets that can be used to train deep learning models.

Therefore, in this study, we use two different modeling approaches to obtain ISAR images of various targets. We use a point scatter (PS)-based model to obtain ISAR images of aircraft, hexacopter drones, and quadcopter drones. Additionally, we employ a three-dimension (3D) mesh-based model to generate ISAR images of birds, quadcopter drones, and unmanned aerial vehicles (UAVs), using physical optics (PO) method to calculate the backscattered field for ISAR imaging. Then, we classify the types of ISAR images using a convolutional neural network (CNN)-based classifier. The proposed classifier incorporates a residual connection structure to address the vanishing gradient issue, which is frequently observed in deep neural network training. Finally, we evaluate the efficiency of our proposed method by verifying the classification accuracy of the proposed deep learning network.

II. Simulation-based ISAR Image Generation

A. PS-based Modeling

When forming ISAR images through simulation, we used two modeling methods: PS-based modeling and 3D mesh-based modeling [11], [12]. In the process of forming an ISAR image through simulation, PS-based modeling represents the target as a collection of discrete scattering centers. Each scattering center contributes to the overall scattered signal, allowing for an effective capture of the target's primary features. This approach uses points to represent the target, simplifying the complex structure by focusing on key aspects that influence the scattered fields. PS-based modeling is efficient and straightforward, making it suitable for cases where an approximate representation of the target is sufficient. However, due to its simplified nature, this approach may lack the precision needed for capturing more intricate geometric details or material properties of the target.

For a target modeled as point scatterers, the backscattered field of the target is calculated based on the distance between the radar and the scattering points that make up the target. The signal reflected from each scattering point includes the time delay and phase changes depending on the time it takes to return to the radar. The signal intensity varies according to the target's position and shape, and there are relative time delay differences between the scattering points. The radar calculates the target's backscattered field by summing the signals received from each scattering point.

B. 3D Mesh-based Modeling

3D Mesh-based modeling represents the target in detail as a polygonal mesh, reflecting more complex geometric structures and surface properties. This modeling method more accurately represents the actual physical shape of the target and considers the influence of complex surfaces, including detailed scattering properties of the object. In this paper, the target material is assumed to be a perfect electric conductor, and this modeling technique enables the simulation of the scattering behavior based on the precise geometric structure of the target.

The target modeled as a 3D mesh uses the PO method to calculate the induced current on the surface of the target [13]–[15]. This current is generated on the surface by the radar's transmitted wave. Then, the radiated wave from the surface current is calculated, and the scattered field is obtained by integrating the radiation over the entire surface of the target.

III. Proposed Deep Learning-based Classifier for ISAR Image

A. Dataset Generation

In this paper, two types of simulation-based ISAR datasets are created to train a deep learning-based classifier. We generate 1,000 images with PS modeling and 90,000 images using 3D mesh modeling for each type of target. The simulation parameters used to generate ISAR images for both PS- and 3D mesh-modeled targets are outlined in Table I. We obtain simulation data for ISAR images of targets across various environments, considering movement velocities, observation times, and signal-to-noise ratios (SNR) [16]–[18]. The velocity of target is set between 10 m/s to 20 m/s, covering typical velocities of the targets (i.e., quadcopter drones, hexacopter drones, aircrafts, birds, and UAVs). Also, the SNR is set between 5 dB to 20 dB with interval of 5 dB. Lastly, the observation time which corresponds to the coherent processing interval (CPI) in real-world ISAR systems, is varied from 1 s to 10 s. Along with aforementioned factors, we also vary the trajectory of targets to generate the ISAR images from multiple look angles. This allow us to create a diverse dataset accounting for the trade-off between image resolution and potential smearing effects due to target motion during the CPI. In our simulation, we assume an X-band radar system. Fig. 1 shows examples of PS-modeled targets and their corresponding ISAR images, and Fig. 2 presents examples of 3D mesh-modeled targets and their corresponding ISAR images.

B. Proposed ISAR Image Classifier

We introduce a residual connection-aided deep learning model designed for efficient classification of various targets from ISAR images. The model leverages residual connections to mitigate the vanishing gradient problem, commonly encountered in the training of deep neural networks. These connections facilitate the unimpeded flow of gradients, thus allowing for the training of deeper architectures without increasing the complexity of network. Our network begins with an input layer for processing ISAR images of size 300×300 in RGB format. It includes an initial 3×3 convolutional layer with 8 filters to capture basic image features. The batch normalization is applied for stability, followed by the rectified linear unit (ReLU) activation to introduce non-linearity into the network. ReLU is chosen for its computational efficiency and its ability to mitigate the vanishing gradient problem, enabling effective training of deep neural networks. Following the initial activation layer, a max-pooling layer is employed to reduce spatial dimensions and computational complexity. Residual block is followed by initial convolution layer, containing two convolutional layers with batch normalization and a shortcut

TABLE I
Parameters Used in ISAR Imaging Radar System

Parameter	Value
Operating band	X-band
Pulse repetition frequency (Hz)	10
Frequency samples	256
Range resolution (cm)	15
Observation time (s)	40
Target velocity (m/s)	$10 \sim 20$
Signal-to-noise ratio (dB)	$5 \sim 20$

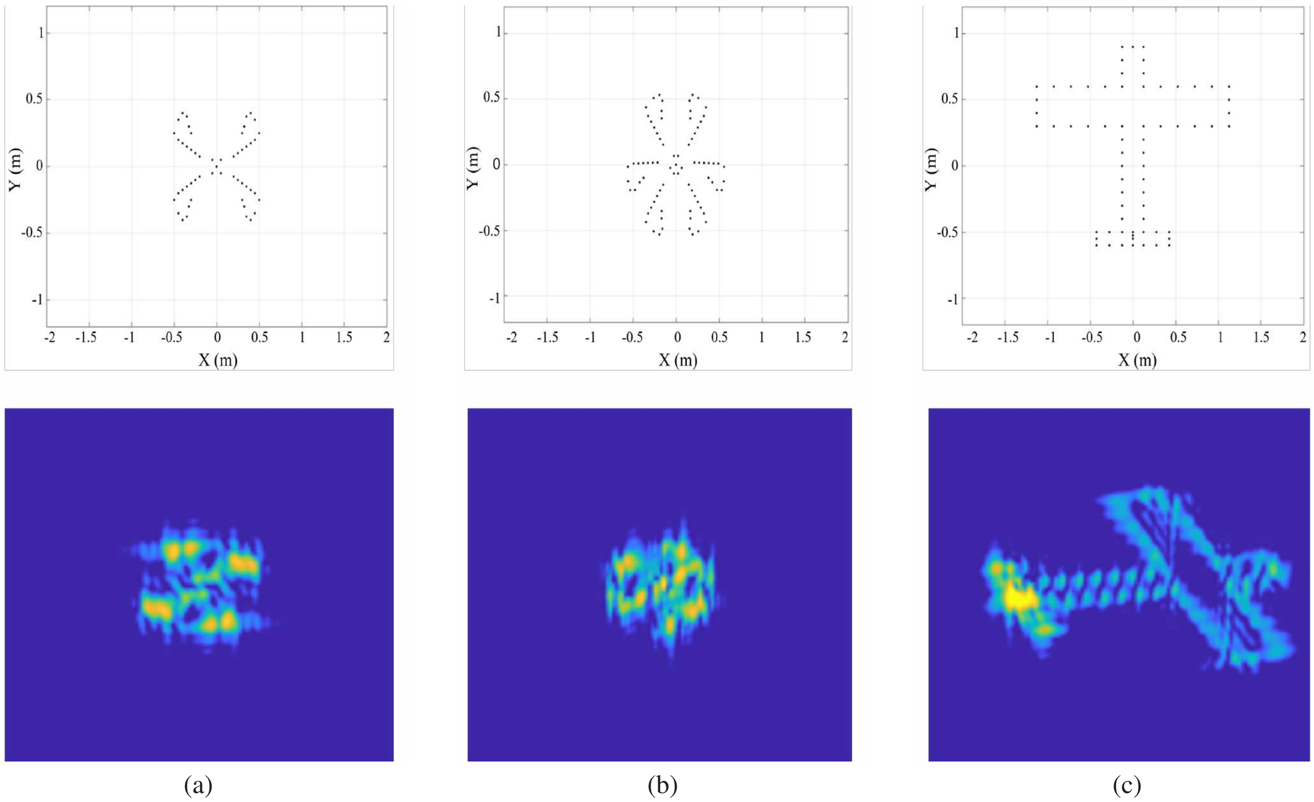


Fig. 1. Example of a PS model and its corresponding ISAR images for (a) a quadcopter drone, (b) a hexacopter drone, and (c) an aircraft.

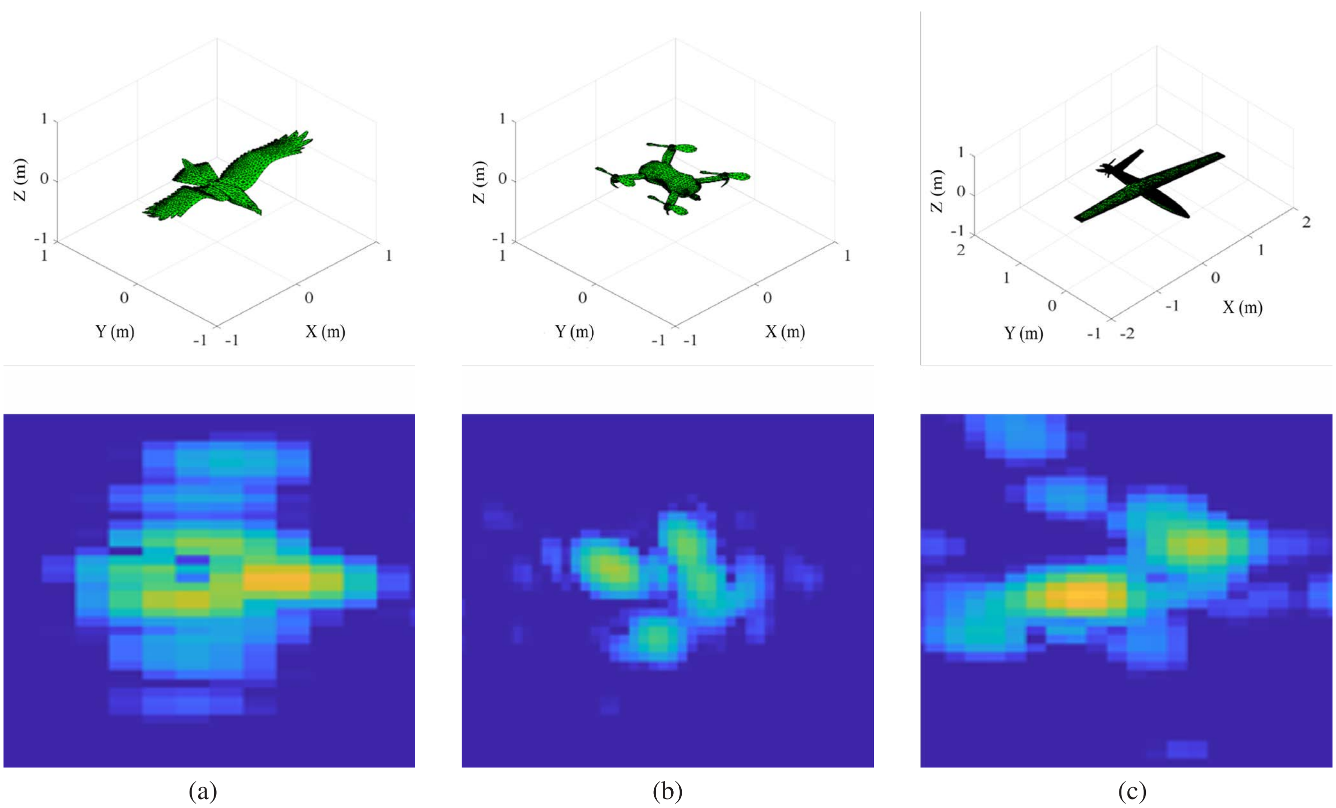


Fig. 2. Example of a 3D mesh model and its corresponding ISAR images for (a) a bird, (b) a quadcopter drone, and (c) UAVs.

connection for dimension alignment. The output of after passing through two consecutive residual blocks is flattened and then passed through a dense layer with 10 ReLU activation functions as an intermediate step before the final classification. Finally, the output layer consists of a dense layer with a softmax activation function, designed to match the number of classes in the training dataset for multi-class classification. We trained the network using cross-entropy loss, and the overall structure of the proposed network is shown in Fig. 3.

C. Performance Analysis

To evaluate the performance of our proposed model, we compared the results with a lightweight CNN model (i.e., reference model) without residual connections. This reference model is selected to analyze the impact of residual connections on classification accuracy and training efficiency. Out of the 1,000 images generated using PS modeling for each target, 80% were used for training, and the remaining 20% were used for validation. For the 90,000 images generated using 3D mesh modeling, the training and validation datasets were separated in the same way. We set the batch size, optimizer, learning rate, and number of epochs identically for the two datasets based on PS and 3D mesh modeling. These parameters were uniformly set at 16, adaptive moment estimation, 0.00001, and 50, respectively, across both the reference and proposed models.

Fig. 4 shows the training results for the PS-based dataset. As shown in Fig. 4 (a), the proposed model achieved higher accuracy for the training and validation datasets compared to the reference model. Additionally, as shown in Fig. 4 (b), the reference model exhibits a difference in loss convergence between the training dataset and the validation dataset. This indicates that the reference model has poor generalization ability to new data. In contrast, the proposed model demonstrates stable loss convergence on both the training and validation datasets.

Fig. 5 shows the training results for the 3D mesh-based dataset. As shown in Fig. 5 (a), although both reference and proposed model show high training accuracies, the proposed model outperforms in terms of validation accuracy. This indicates that our proposed method can guarantee better generalization performance when processing new ISAR images. Moreover, as shown in Fig. 5 (b), the proposed model exhibits stable loss convergence for both the training and validation datasets. The reference model has performance limitations

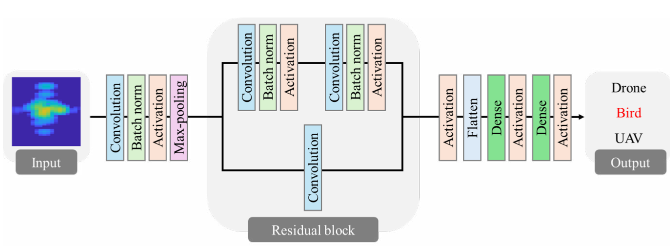


Fig. 3. Overall structure of the proposed deep learning network.

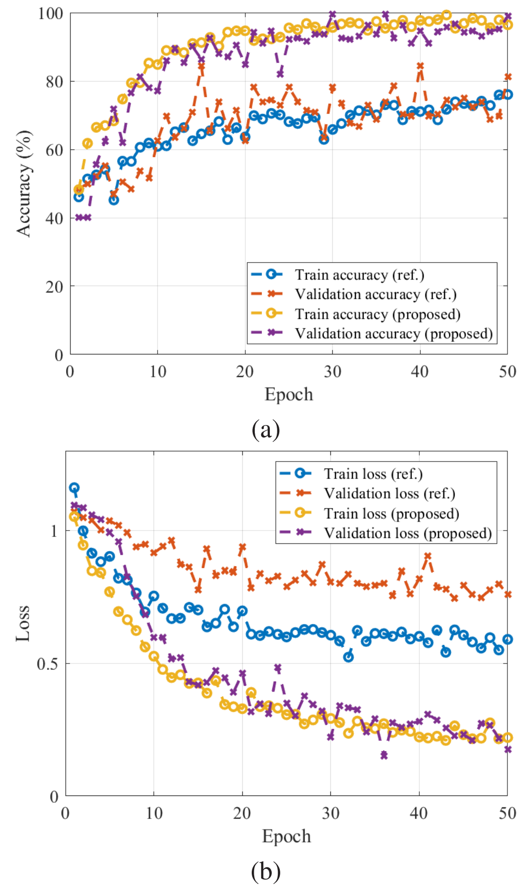
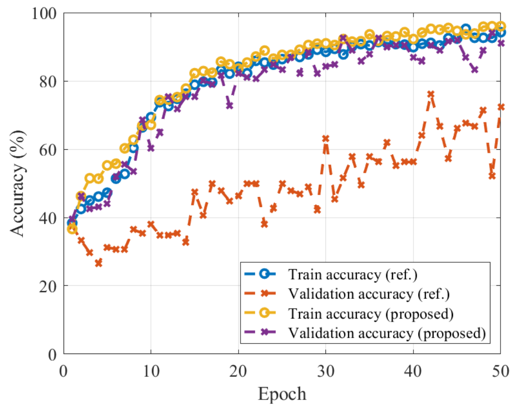


Fig. 4. Comparison of the reference model and the proposed model on the PS dataset: (a) accuracy and (b) loss.

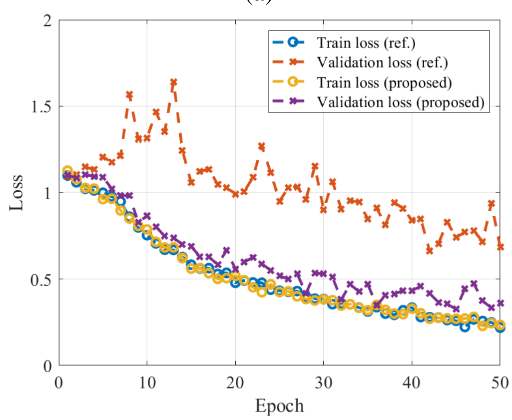
with new datasets. In contrast, the proposed deep learning network classified targets with 98% accuracy on the PS-based dataset and achieved 96% accuracy on the 3D mesh-based dataset, demonstrating strong performance even when applied to new datasets. This suggests that the model generalizes well and is capable of maintaining high accuracy across different types of data. Although the PS-based dataset resulted in higher classification accuracy because it is more ideal than the 3D mesh-based dataset, the classification accuracy of the 3D mesh-based dataset is still high.

D. Evaluation on Real ISAR Data

We evaluated whether the proposed model can effectively identify targets in real ISAR images. When we input 460 real ISAR images of a quadcopter drone into the proposed model, it achieved 100% accuracy across all scenarios, regardless of whether the model was trained on PS-based or 3D mesh-based datasets. Although this test was limited to a single type of image, it provided critical initial validation of the model's performance on real-world data. These results suggest that the proposed model may have a certain level of applicability to real-world data, and further testing with additional image types and under varying conditions could help strengthen its reliability.



(a)



(b)

Fig. 5. Comparison of the reference model and the proposed model on the 3D mesh dataset: (a) accuracy and (b) loss.

IV. Conclusion

In this paper, we proposed a deep learning network designed to effectively classify various types of ISAR images. First, we conducted simulations using two distinct modeling techniques: PS and 3D mesh. Through this approach, the proposed network was trained and validated on each dataset, achieving a high classification accuracy of 98% on the PS-based dataset and 96% on the 3D mesh-based dataset. Furthermore, when comparing the performance of the proposed network with that of a lightweight CNN model without residual connections, the proposed network demonstrated an average classification accuracy improvement of 17%p on the PS-based dataset and 25%p on the 3D mesh-based dataset.

Additionally, in a further test using real ISAR images of a quadcopter drone as input data, the proposed model successfully classified these images as quadcopter drones. Although this test was limited to a single type of image, it provides important initial validation of the proposed deep learning network's applicability to real-world data. Future experiments with different image types and conditions could demonstrate the model's reliability. This study suggests that the proposed deep learning network can be effectively utilized to accurately classify ISAR images of airborne targets under practical conditions.

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