JOURNAL OF SCIENCE, TECHNOLOGY AND ENGINEERING RESEARCH
Bilim, Teknoloji ve Mühendislik Araştırmaları Dergisi
ISSN (Online) 2717-8404
Available *online* at https://dergipark.org.tr/en/pub/jster

RESEARCH ARTICLE

Drone Swarm Classification from ISAR Imaging

*Remziye Busra Coruk, [1]Ali Kara, and [2] Elif Aydin

*Atilim University, Faculty of Engineering, Electrical and Electronics Engineering Department, Ankara, Turkey
rbusratezel@gmail.com, Orcid.0000-0002-9466-3862
[1]Gazi University, Faculty of Engineering, Electrical and Electronics Engineering Department, Ankara, Turkey
akara@gazi.edu.tr, Orcid.0000-0002-9739-7619
[2]Cankaya University, Faculty of Engineering, Electrical and Electronics Engineering Department, Ankara, Turkey
elif.aydin@cankaya.edu.tr, Orcid.0000-0001-6878-1796

Citation:
Coruk, R. B., Kara, A., Aydin, E. (2024). *Drone Swarm Classification from ISAR Imaging*, Journal of Science Technology and Engineering Research, 5(2): 127-134. DOI: 10.53525/jster.1529575

HIGHLIGHTS

- *ISAR images of drone swarms are created based on various formation types*
- *Radar and simulation parameters are adjusted to achieve high resolution*
- *Formation types of drone swarm are classified with deep learning algorithm*
- *The developed method can be used for anti-drone technologies*

Article Info

Received : August 7, 2024
Accepted : September 23, 2024

DOI:
10.53525/jster.1529575

***Corresponding Author:**
Remziye Busra Coruk
rbusratezel@gmail.com

ABSTRACT

The use of drones has become increasingly popular as they can be easily purchased over the Internet. As drones find applications in a variety of fields, drone swarms have also gained significance. However, this popularity has introduced some challenges, particularly in the realm of drone detection, which is crucial for preventing the uncontrolled use of drone swarms in airspace. Drone swarm detection is essential to avoid dangerous accidents or criminal acts. This paper presents an inverse synthetic aperture radar (ISAR) imaging-based approach for identifying the formation types of drone swarms. The ISAR images of drone swarms are generated by using commercial an EM tools including ANSYS. High frequency structural simulator (HFSS) - shooting bouncing ray (SBR+) solver is used for fast computation. The radar operation, as well as simulation configuration necessary for generating usable ISAR images, are quantified. In particular, the down-range and cross-range resolutions are evaluated to achieve high resolution images. The ISAR images are classified based on pre-defined swarm formations using deep learning. To this end, a convolutional neural network (CNN) model is employed. The model consists of training, validation, and testing phases. The swarm formation classes include Line, Square, Cross, and Triangle. The results demonstrate high accuracy in classification performance. The developed method can be utilized in anti-drone technologies.

Keywords: *Radar Systems, Inverse synthetic aperture radar imaging, Drone, Classification, Convolution neural network*

I. INTRODUCTION

Drones are defined as one of the Unmanned Aerial Vehicles (UAVs) that can be controlled remotely and automatically. Nowadays, they are widely used due to their easily accessible features. With the widespread use of drones, some rules and regulations have emerged to prevent the uncontrolled use of drones in the airspace. And, detecting drones that do not comply with these rules has become important. In addition, the use of drones in the military along with civil has become prevalent today. Thus, drone detection has also gained popularity in both civil and military fields [1]. By operating in a group, drones can combine their individual capabilities to deliver superior capabilities and tackle defined missions. Moreover, even if they are within the herd, they can also undertake different tasks individually defined for themselves. With these versatile capabilities, drone swarms have become popular nowadays [2].

Radar, electro-optical, and camera systems among the developing world technologies, are used for reconnaissance and surveillance purposes. The ability of radar systems to detect objects at long distances even in bad weather conditions makes them more selectable in recently developed systems. Consequently, the usage of radar systems to detect drones flying in the airspace is more common in the literature [3]. To detect the targets, there are two methods of radar systems. These are the frequency measurement method [4] and the range (time) measurement method [5]. While the frequency measurement method measures the micro-doppler of drones, the range (time) measurement method creates imaging of a drone by synthetic aperture radar (SAR) or the inverse-SAR (ISAR). SAR allows obtaining high-resolution images of the earth's surface even in bad weather conditions [6]. ISAR, on the other hand, provides information about targets such as ships, aircraft, and UAVs by obtaining images of moving targets [7]. SAR/ISAR systems are used by deploying to ground stations or manned/unmanned aerial platforms such as aircraft or satellites.

ISAR imaging is a topic that has attracted much attention in radar imaging technology in recent years. In ISAR technology, there is target movement, and this movement changes the direction of the target relative to the radar system, resulting in different aspect angles of viewing the target. Afterward, the backscatter signal of each reflection point of the target undergoes a phase change. Coherent data processing, as in SAR, provides high spatial resolution even in the azimuthal direction [8]. ISAR images for drone targets have been investigated in the literature. In [9], drone types of different sizes are detected by radar. Drones are made to rotate according to the radar by using a turntable. Thus, the radar data is processed to obtain an ISAR image of the target. In ISAR results, images of the drone at different frequency values, viewing angles, and also various polarization modes are analyzed and interpreted. In the other work [10], the authors present radar cross section (RCS) and ISAR image results of the fixed-wing drone. Experiments are carried out in an anechoic chamber using fully polarimetric radar. The authors show the effects of different parts of the drone based on four polarization modes. In [11], 2D and 3D ISAR images are reconstructed to identify flying drones. Sparse recovery techniques are used to create 2D ISAR images. Finally, 3D ISAR image of the drone is created using interferometry. The study includes measurement results. In [12], the authors emphasize the importance of ISAR imaging for the classification of drone targets. High-resolution images are reconstructed using multi-band radar. Both theoretical and experimental analyses are conducted on drones, and the results are analyzed and compared. In [13], the authors propose a method that uses ISAR images to classify drone targets. The polar mapping procedure is important to obtain the features of targets for the classifier. Experimental results are presented to show the differences between distorted and undistorted images. In [14], the authors propose a new algorithm to classify drone types (a commercial quadcopter and its explosive-loaded version). The authors propose an approach in security-sensitive environments for drones. On the other hand, the detection and recognition of drone swarms have not been studied much. In [15], the drone formation types are classified based on navigation data. The machine learning classification is employed. In today's technology, the usage of drone swarm structures has increased considerably in both civilian and military fields. With the increase in the use of drone swarm structures, it has become important to develop drone swarm detection algorithms to prevent their illegal use and to ensure that they are moved in the airspace in a controlled manner. However, the detection of drone swarms especially using ISAR images is limited in the literature. Additionally, the classification of drone swarms using ISAR images with a deep learning

algorithm with high accuracy and a small dataset is not available at all in the literature.
This paper presents an approach, based on ISAR images, to the problem of classification of drone swarms. The ISAR images are reconstructed using commercially available software tools, including ANSYS. Imaging radar configuration and simulation parameters are analyzed to achieve higher resolution. ISAR images are created based on several formations of drone swarms including Line, Square, Cross, and Triangle. A convolutional neural network (CNN) is proposed for the classification of drone swarms. Some preliminary results of the classification performance are presented.

The remainder of this paper is organized as follows; Section II presents the proposed method including a review of image formation concepts, radar configuration, and simulation parameters as well as the classification process. Section III presents the results of the classification of drone swarm formations, and finally, Section IV draws some conclusions.

II. METHOD

A. ISAR Image Formation

The reflected radio frequency signals from the target to the radar are processed with the ISAR technique. The Inverse Fourier Transform (IFT) is applied to the signal and the reflectivity density function which express the ISAR image of the target is generated by the following equation

$$\rho(x,y) = IFT\{S_R(t)\exp\left[-j4\pi f\,\frac{R(t)}{c}\right] \tag{1}$$

$S_R(t)$ is the return signal to radar from the target, $R(t)$ is the distance from the radar to the point target at time t (sn), f (Hz) is the frequency, and c (m/sn) is the speed of light [16].

B. Radar and Simulation Parameters

Millimeter wave (mmWave) radars are widely used for high resolution imaging applications. Obtaining high-resolution ISAR images of targets is important for detecting objects with high accuracy. High resolution depends on accurate calculation of the mmWave radar's down-range and cross-range resolution. Considering the synthetic aperture created by the radar on the target, the component in the direction of the radar is called down-range, and the component parallel to the flight line is called cross-range. While down-range resolution is dependent on bandwidth $(\frac{c}{2B})$ while cross-range is dependent on both the synthetic antenna aperture and the range $(\frac{\lambda\, R}{2D_s})$ [16].

High frequency structural simulator (HFSS) within ANSYS software platform is utilized in this study. HFSS-SBR+ which is an asymptotic high-frequency electromagnetic (EM) simulator is used for generating ISAR images. The shooting and bouncing ray (SBR+) technique is preferred due to its highly efficient and an accurate computation of complex EM scattering mechanisms. Here, the configuration of the radar and simulation parameters are important for high resolution ISAR imaging [17]. Frequency (MHz) and angle steps (degree) are formulated, respectively, as follows

$$\Delta f = \frac{c}{2\,x_{max}} \tag{2}$$

$$\Delta\varphi = \frac{\lambda}{2\, y_{max}} \tag{3}$$

where x_{max} (m) is the down range extent while y_{max} (m) is the cross range extent, and λ (m) is the wavelength. Also, bandwidth (MHz) and aspect angle (degree) parameters are formulated, respectively, as follows

$$B = \Delta f\ N_x \tag{4}$$

$$\Delta\phi = \Delta\varphi\ N_y \tag{5}$$

where N_x is the number of samples in x-axis and N_y is the number of samples in y-axis.

C. Classification of images

Deep learning has attracted a lot of attention in recent years and occupies a large place in the literature. Deep learning methods are also used for image classification in the literature. One of the most common is CNN in image classification, and it is utilized in this research. When briefly reviewing, CNN is a specialized neural network for processing and classification of image data. CNN processes the image with several layers [18]. CNN layers are listed below:

1) Convolutional Layer
This layer of the CNN model is the most important and indispensable layer. It is responsible for extracting the features of the image. It applies filtering techniques to extract low and high-level features in the image.
2) Pooling (Down-sampling) Layer
A pooling layer is added between successive convolutional layers. It takes on the task of reducing parameters and computational complexity. Max pooling, average pooling, and L2-norm pooling methods are frequently used, but the most popular one is max pooling.
3) Flattening Layer: This layer of the CNN prepares the data for the input of the last layer, the fully connected layer. The data are the matrixes coming from the convolutional and pooling layers converted into a one-dimensional array.
4) Fully-Connected Layer: Fully-connected layer is the most important layer of the CNN model. It performs the process of learning the data prepared by the flattening layer through the neural network.

III. RESULTS

ISAR images are reconstructed based on various scenarios of swarms using ANSYS software. Five bounces are used to simulate the ISAR images. For the physical theory of diffraction (PTD), the edge density of 20 edge segments/wavelength is considered. Radar parameter values are important for high-resolution ISAR images. Radar is operated at mmWave frequency band (77 GHz). ISAR image size is adjusted as 5 m×5 m. Additionally, down-range and cross-range resolution parameters are selected as 0.05 m. Based on the radar configuration, the simulation parameters are estimated including frequency step, angle step, bandwidth, and aspect angle. The drone type is specified as a quadcopter in the swarm. Computer aided design (CAD) model of drone is created as in Fig.1.

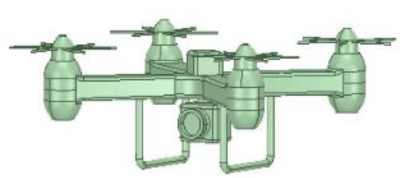

Figure. 1. CAD model of drone

Drones follow the rules of swarm structures and fly synchronously with other drones by following the same formation in the swarm structure. A drone swarm is composed of a static structure with a generally adopted geometric shape [19-21]. Drone swarm scenarios are designed by considering several formation types (Line, Square, Cross, and Triangle). Formation types of drone swarms at various look angles can be examined in Fig. 2.

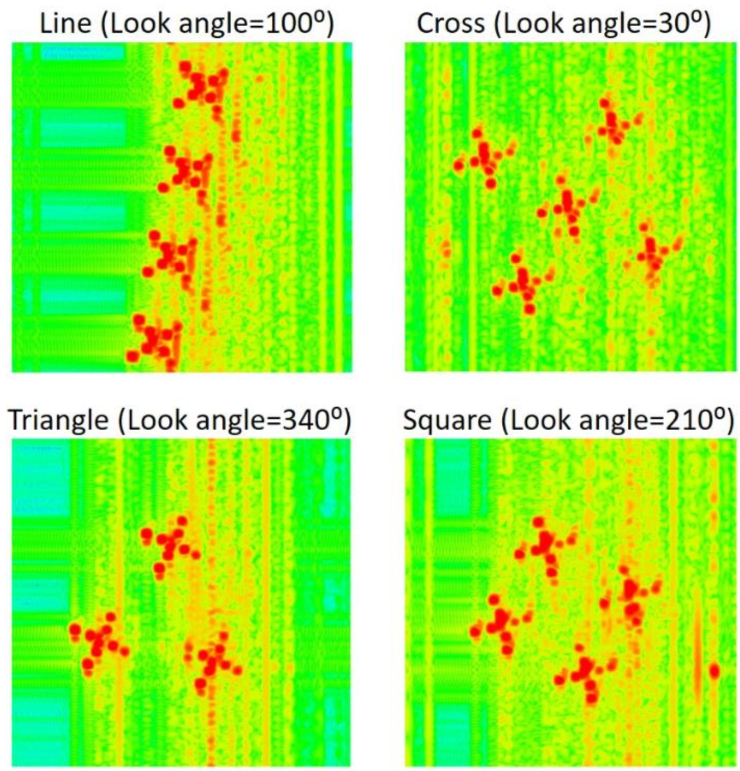

Figure. 2. Formation types of drone swarm

Due to the deep learning algorithm requirements, it is important to study large data sets to solve the classification problem with high accuracy without the need for deep networks. Therefore, it is important to expand the high-resolution ISAR image data, obtained for the drone swarms, for use in the deep learning algorithm. CNN model is used to classify ISAR images of drone swarms, because it is the most useful model for the image classification problem. The basic CNN model is selected for the classification part to avoid computational complexity. The dataset is extended by creating ISAR images between 0º and 350º with 10º intervals. A total of 140 ISAR images are used. The dataset is divided into training, validation, and testing phases to increase performance (80% training, 10% validation, 10% testing). ISAR images of drone swarms are trained with 30 epochs. The convolutional layers in the model use 3×3 kernel filters. Rectified linear units (ReLU) are used as the activation function in the convolutional layers, while the softmax activation function is applied in the last layer of the CNN model. Additionally, the batch size is set to 32. Google Colab environment, which allows to write python code, is used to create CNN algorithms. CNN model is given in Fig. 3.

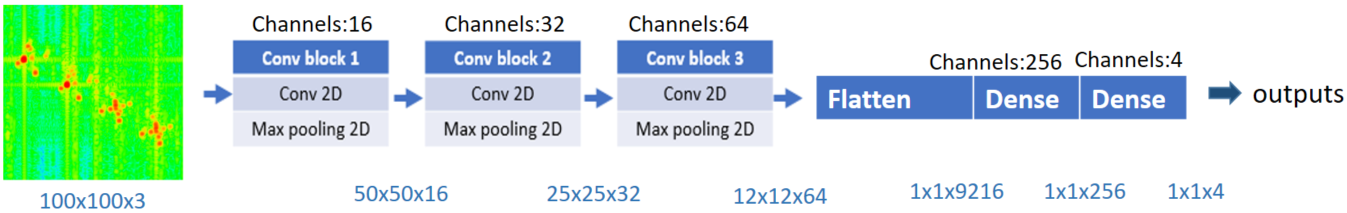

Figure. 3. Layers of the CNN algorithm

ISAR images are trained using CNN model. The plotting of the accuracy results versus epoch is given in Fig. 4.

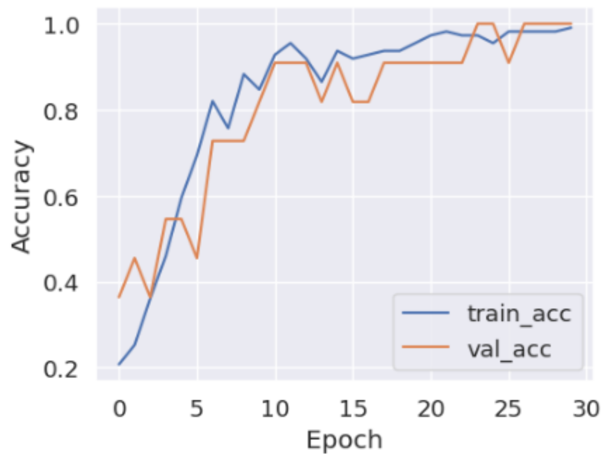

Figure. 4. Accuracy Results versus epoch

Training and validation performances improve as the number of epochs increases, reaching the highest at the end. To test the model's performance, the four ISAR images shown in Figure 2 are used. The test results are provided with confusion matrix given in Figure 5.

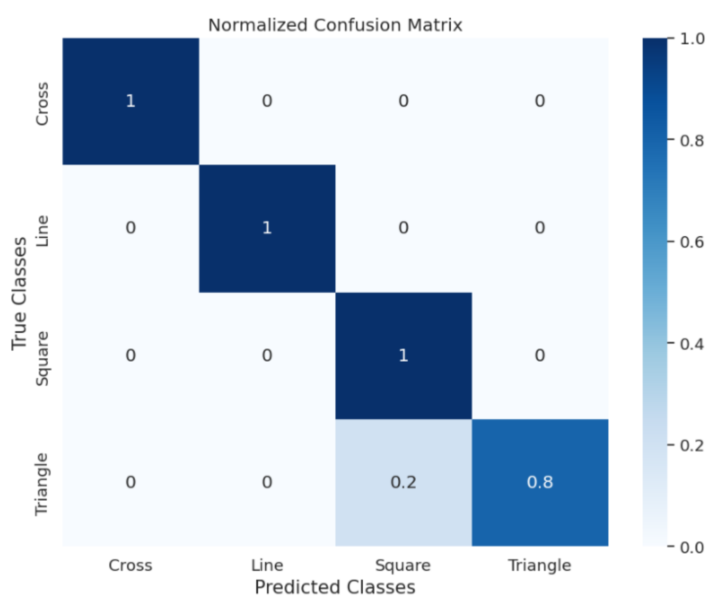

Figure. 5. Confusion matrix for test step

As a result, the classification performance of the model, which is trained with ISAR images based on various formation swarm types, is presented. Based on the confusion matrix, test accuracy is 95%. Triangle-Square formation types are confused for one image. Promising results have been obtained for future drone swarm classification studies.

IV. CONCLUSION

The classification of the formation of drone swarms remains a challenging problem when datasets created from ISAR images are used. This paper presents an approach for detecting drone swarm formations using ISAR images. Drone swarms are created based on several formation types including Line, Square, Cross, and Triangle. The dataset includes reconstructed ISAR images of scenarios from different look angles (ranging from 0° to 350° in 10° intervals) to ensure angular diversity. Radar and simulation parameters are quantified in image reconstruction in order to achieve high-resolution imaging. ISAR image dataset is divided into training, validation, and testing phases (80%-10%-10%) to prevent overfitting. The model is trained using a CNN algorithm, and an acceptable classification performance is demonstrated. The developed method can be used for anti-drone technologies.

As the paper presents some preliminary results of ongoing research, the future work will focus on extending the ISAR image dataset to include diverse scenarios (such as various drone sizes and with and without payload configurations) to further improve performance for more realistic operations. Furthermore, some more complex classification methods will be developed, and comparative results will be presented.

CONFLICTS OF INTEREST

They reported that there was no conflict of interest between the authors and their respective institutions.

RESEARCH AND PUBLICATION ETHICS

In the studies carried out within the scope of this article, the rules of research and publication ethics were followed.

REFERENCES

[1] Coluccia, A., Parisi, G., & Fascista, A. (2020). Detection and classification of multirotor drones in radar sensor networks: A review. Sensors, 20(15), 4172. doi: 10.3390/s20154172

[2] Tang, J., Duan, H., & Lao, S. (2023). Swarm intelligence algorithms for multiple unmanned aerial vehicles collaboration: A comprehensive review. Artificial Intelligence Review, 56(5), 4295-4327. doi: 10.1007/s10462-022-10281-7

[3] Ciattaglia, G., Temperini, G., Spinsante, S., & Gambi, E. (2021, June). mmWave Radar Features Extraction of Drones for Machine Learning Classification. In 2021 IEEE 8th International Workshop on Metrology for AeroSpace (MetroAeroSpace) (pp. 259-264). IEEE. doi: 10.1109/MetroAeroSpace51421.2021.9511703

[4] Chen, V. C. (2019). The micro-Doppler effect in radar. Artech house.

[5] Franceschetti, G., & Lanari, R. (2018). Synthetic aperture radar processing. CRC press.

[6] Gökdoğan, B. Y., Çoruk, R. B., Aydın, E., & Kara, A. 2D Millimeter-Wave SAR Imaging with Automotive Radar. Journal of Science, Technology and Engineering Research, 5(1), 68-77.

[7] Borkar, V. G., Ghosh, A., Singh, R. K., & Chourasia, N. (2010). Radar cross-section measurement techniques. Defence Science Journal, 60(2), 204-212. doi: 10.14429/dsj.60.341

[8] Yang, Y., Wang, X. S., Li, Y. Z., & Shi, L. F. (2019, September). RCS measurements and ISAR images of fixed-wing UAV for fully polarimetric radar. In 2019 International Radar Conference (RADAR) (pp. 1-5). IEEE. doi: 10.1109/RADAR41533.2019.171361

[9] Li, C. J., & Ling, H. (2016). An investigation on the radar signatures of small consumer drones. IEEE Antennas and Wireless Propagation Letters, 16, 649-652.

[10] Yang, Y., Wang, X. S., Li, Y. Z., & Shi, L. F. (2019, September). RCS measurements and ISAR images of fixed-wing UAV for fully polarimetric radar. In 2019 International Radar Conference (RADAR) (pp. 1-5). IEEE.

[11] Hamad, A., & Berens, P. (2024, July). 3D ISAR Imaging of an in-Air Rotating Drone Using Sparse Recovery and Multi-Channel Interferometry. In 2024 International Radar Symposium (IRS) (pp. 358-362). IEEE.

[12] Lee, W. K., & Song, K. M. (2018, August). Enhanced ISAR imaging for surveillance of multiple drones in urban areas. In 2018 International Conference on Radar (RADAR) (pp. 1-4). IEEE.

[13] Kim, K. T., Seo, D. K., & Kim, H. T. (2005). Efficient classification of ISAR images. IEEE Transactions on Antennas and Propagation, 53(5), 1611-1621.

[14] Sayed, A. N., Ramahi, O. M., & Shaker, G. (2024). In the Realm of Aerial Deception: UAV Classification via ISAR Images and Radar Digital Twins for Enhanced Security. IEEE Sensors Letters.
[15] Barbeau, M. (2019). Recognizing drone swarm activities: Classical versus quantum machine learning. Digitale Welt, 3(4), 45-50.
[16] Chen, V., & Martorella, M. (2014). Inverse synthetic aperture radar imaging: principles, algorithms and applications. IET. doi: 10.1049/SBRA504E
[17] "ANSYS HFSS SBR+" https://www.ansys.com/content/dam/resource-center/application-brief/ansys-sbr-plus.pdf (accessed: Dec 18, 2023).
[18] Ketkar, N., Moolayil, J., Ketkar, N., & Moolayil, J. (2020). Deep Learning with Python: Learn Best Practices of Deep Learning Models with PyTorch. Apress LP.
[19] Alkouz, B., Abusafia, A., Lakhdari, A., & Bouguettaya, A. (2022). In-flight energy-driven composition of drone swarm services. IEEE Transactions on Services Computing, 16(3), 1919-1933.
[20] Adoni, W. Y. H., Lorenz, S., Fareedh, J. S., Gloaguen, R., & Bussmann, M. (2023). Investigation of autonomous multi-UAV systems for target detection in distributed environment: Current developments and open challenges. Drones, 7(4), 263.
[21] Alkouz, B., & Bouguettaya, A. (2020, December). Formation-based selection of drone swarm services. In MobiQuitous 2020-17th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (pp. 386-394). doi: 10.1145/3448891.3448899