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Range–Doppler Map-Based Multi-Object Estimation in OFDM Radar Using YOLOv8

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***Abstract*—This paper proposes a technique that employs the YOLOv8 deep learning model to simultaneously estimate the number, distance, and velocity of multiple objects in an orthogonal frequency division multiplexing (OFDM) radar system. The two-dimensional range-Doppler map generated from the OFDM radar signal is used as input to the YOLOv8 model for object distance and velocity estimation. Simulation results demonstrate that the proposed method outperforms the YOLOv5-based approach, particularly achieving lower estimation errors under low-SNR conditions. Since the method relies solely on two-dimensional range-Doppler data, it can be effectively applied to future communication-radar fusion systems in next-generation (6G) networks.**

Keywords—OFDM Radar, YOLOv8, Multi-Object Estimation, Range-Doppler map, Distance, Velocity

I. INTRODUCTION

In today's wireless communication environment, the competition for frequency resources between radar and communication systems underscores the need for integrated solutions that can perform both functions simultaneously. Orthogonal frequency division multiplexing (OFDM)-based radar enables sensing without requiring dedicated spectrum, as it reuses existing communication signals. By exploiting the orthogonal subcarriers of OFDM, a range-Doppler map can be generated to extract object distance and velocity. However, in complex multi-object scenarios, traditional constant false alarm rate (CFAR)-based peak detection methods are insufficient [1]. In particular, object separation and parameter estimation accuracy degrade significantly when multiple objects are closely spaced under low signal-to-noise ratio (SNR) conditions.

This paper proposes an algorithm that estimates the number, distance, and velocity of multiple objects by applying the YOLOv8 deep learning model to the two-dimensional range-Doppler map of an OFDM radar system. Prior studies primarily employed YOLOv5 [2], and this work compares the performance of YOLOv5 and YOLOv8. Experimental results demonstrate that the YOLOv8-based approach outperforms YOLOv5, especially in maintaining stable estimation accuracy under low-SNR conditions.

II. INTRODUCTION

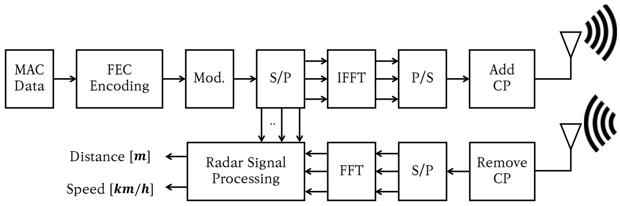

Fig. 1. OFDM Radar System Model

Figure 1 illustrates the structure of the OFDM radar system. At the transmitter, modulated data symbols are converted into time-domain OFDM symbols using the IFFT (Inverse Fast Fourier Transform), after which a cyclic prefix (CP) is inserted before transmission over the wireless channel. The transmitted signal is delivered to the communication receiver and simultaneously reflected by target objects, which are then received by the radar receiver. At the receiver, the CP is removed and an FFT is applied to transform the signal into the frequency domain. Accumulating over M consecutive OFDM symbols produces an $M \times N$ time–frequency matrix, where N denotes the number of subcarriers. The time axis represents temporal correlations across symbols, while the frequency axis represents the frequency response of the subcarriers, both of which are exploited for range and velocity estimation. Applying FFTs along the range and Doppler dimensions yields a two-dimensional range-Doppler map, in which each object appears as a peak at a specific range–Doppler bin. In this work, the range-Doppler map is treated as an image, and a deep learning–based object detection method is applied to simultaneously estimate the number, range, and velocity of multiple objects.

III. PROPOSED METHOD

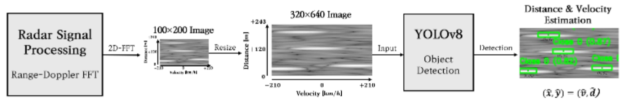

Fig. 2. Proposed multi-target estimation algorithm

This study proposes an algorithm that simultaneously estimates the number, distance, and velocity of multiple objects, which uses two-dimensional range-Doppler maps generated from an OFDM radar system as input to the YOLOv8 model. Figure 2 illustrates the overall framework of the proposed multi-object estimation algorithm. This approach enables distance and velocity estimation without the need for additional input data beyond the range-Doppler map.

IV. SIMULATION

This study uses MATLAB to generate training data and employs a TensorFlow-based deep learning framework to train and validate the YOLO model. The simulation environment of the OFDM radar system is configured as follows: The OFDM symbol duration is approximately 35.74 μs, and the sampling frequency is 122.88 MHz. The IFFT size is 4096, the system bandwidth is 40 MHz, and the carrier centre frequency is 28 GHz. The cyclic prefix length is 296 samples, and the number of OFDM symbols was varied across 2, 4, and 8. The 2D FFT size was set to 2048×256, and the cropped region of the range-Doppler map was 100×200. The simulation considered 1 to 5 targets and an SNR range from -10 dB to 20 dB. A total of 50,000 training samples and 110,000 test samples were generated. The hyperparameters for YOLO model training are summarised in Table 1, organised by model version and symbol count. Early stopping was applied to all models to prevent overfitting. The performance metric was the mean absolute error (MAE).

TABLE I. HYPERPARAMETERS BY MODEL VERSION

parameters	***Values***					
	YOLOv5			***YOLOv8***		
Model version	***2 symbol***	***4 symbol***	***8 symbol***	***2 symbol***	***4 symbol***	***8 symbol***
Bounding-box	60×6	50×6	40×8	60×6	50×6	40×8
Learning rate	0.001	0.01	0.001	0.01	0.001	0.01
Batch size	16	32	32	32	32	32
Epoch	100	200	100	100	100	100
Optimizer	SGD	SGD	Adam	SGD	Adam	SGD

Figures 3 and 4 show the performance of YOLOv5 and YOLOv8 in estimating distance and velocity for different numbers of objects as a function of SNR. The results indicate that across all symbol counts and multi-object scenarios, YOLOv8 consistently outperforms YOLOv5. The performance gap is especially evident under low symbol counts and low-SNR conditions. For example, with eight OFDM symbols and five objects, YOLOv5 recorded average distance and velocity errors of 0.91 m and 2.06 km/h, while YOLOv8 achieved 0.70 m and 1.85 km/h. This demonstrates a significant reduction in error. As the number of symbols increased, both models exhibited decreasing velocity estimation errors; however, YOLOv8 achieved a greater reduction and higher overall accuracy. These results suggest that YOLOv8 enables robust and accurate distance and velocity estimation even in complex communication environments.

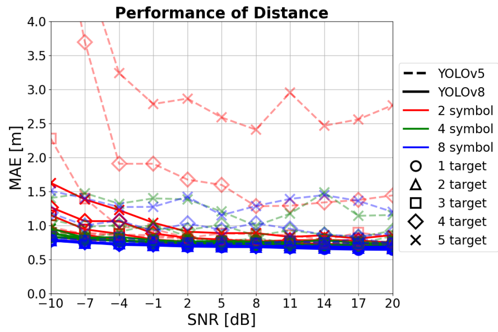

Fig. 3. MAE of multi-object distance estimation versus SNR

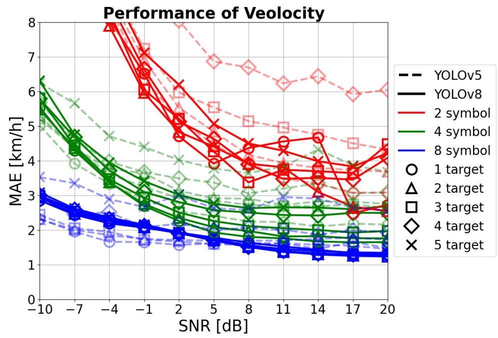

Fig. 4. MAE of multi-object velocity estimation versus SNR

V. CONCLUSION

In this paper, we proposed a YOLOv8-based method for simultaneously estimating the distance and velocity of multiple objects in an OFDM radar system. By treating the two-dimensional range-Doppler map as input to YOLO, the proposed approach enables accurate parameter estimation without additional signal processing. Simulation results confirmed that the method outperforms YOLOv5, particularly under low-SNR and multi-object conditions, demonstrating robust performance in complex environments. These results highlight the potential of the proposed method as a foundation for next-generation communication–sensing fusion systems that integrate radar and communication functions.

REFERENCES

[1] M. M. Al-Dabaa, E. Laslo, A. A. Emran, A. Yahya, and A. Aboshosha, “Multiple targets CFAR detection performance based on an intelligent clustering algorithm in K-distribution sea clutter,” *Sensors*, vol. 25, no. 8, p. 2613, Apr. 2025.

[2] E. A. Ko, S. Y. Jeon, and E. R. Jeong, “Multi-object detection and range/velocity estimation in OFDM radar system using YOLOv8,” in Proc. Symp. Korean Inst. Commun. Inf. Sci. (KICS), Jeju, Korea, Jun. 2025, pp. 277-278.