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Comparison of CW Radar Systems for Radar Applications using Object Detection and Real-Time Tracking

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***Abstract*—Since their prevalence in World War II, Radar-based systems have provided a strategic advantage for military applications. Since then, radars have merged into everyday commercial products ranging from Automotive sensors for adaptive cruise control, to home security systems used to protect one's home. Due to their various use cases for pattern recognition, classification, and Computer Vision tasks, many radar-systems incorporate machine learning models. This paper aims to implement a real-time tracking system comprised of a low-cost transceiver and Computer Vision model. To determine the most optimal setup, the study will compare implementations that include two low-cost transceivers and two different weights from the YOLOv3 algorithm. The comparison will determine the most optimal constraints for the tracking system by measuring system latency, and classification confidence.**

Keywords—Radar Transceiver, HB100, CDM324, Constant False Alarm Rate, Computer Vision, YOLOv3, Object Detection, System Latency, Average Classification

I. INTRODUCTION

A. Overview

When an individual walks into the transceiver's detection zone, the radar system tracks them using real-time object detection and speed monitoring via the doppler shift [13]. Achieving this outcome requires meeting the requirements of two objectives from both the hardware and software domains. The first objective is to detect the presence of an individual and track their speed within the transceiver's detection zone. The speed is tracked, and the history is analyzed using a combination of the doppler shift and a Constant-False Alarm Rate, (CFAR) algorithm. The CFAR algorithm is a cell averaging method used for detecting changes from the radar receiver to track and analyze the target's behavior, with respect to an established threshold.

The second objective requires establishing a serial communication with the Raspberry Pi4 to feed data into a python script that performs its Computer Vision task in real time using the YOLOv3 algorithm.

The YOLOV3 algorithm is a popular choice for many Computer Vision models [3]. This study aims to examine the tradeoffs between two types of YOLOv3 models; The YOLOv3-608 and the YOLOv3-tiny models, each of which come with their own set of weights and configuration. The YOLOv3-608 model is considered to provide the most accuracy with a mean Average Precision of 57.9 and 20 frames per second. On the other hand, the YOLOv3-tiny model delivers more speed with 220 frames per second while including a tradeoff of less accuracy with 33.1 mean Average Precision. An optimal radar system takes these tradeoffs into consideration with the goal of finding the most efficient system of detecting and tracking human presence, given our low-cost setup.

B. Related Works

Since our main focus is a low-cost setup with an efficient detection and tracking system, this paper will utilize the knowledge and implementation of past radar applications. For example, a rocket tracking method proposed by [1] is a study on a moving target tracking algorithm based on Computer Vision. [2] also uses Computer Vision but focuses more on human target detection and abnormal behavior recognition to record suspicious individuals through the use of a camera.

As YOLOv3 is a vital component in this Computer Vision model and [3] has already compared YOLOv3-320 with YOLOv3-tiny, this paper will compare YOLOv3-608 and YOLOv3-tiny. Therefore, unlike [4], which improved upon YOLOv3 based on a lightweight network, this paper will choose which YOLOv3 algorithm has an optimal tradeoff of speed and efficiency while using a low-cost setup. While this experiment focuses on tracking an individual human target, another related work uses the YOLOv3 algorithm for pedestrian target recognition [5]. Another popular Computer Vision model is the SSD MobileNet algorithm, which is also known for its speed of detection and object identification performance. A comparison between the SSD and YOLOv3 algorithm showed that the YOLOv3 model displayed a better performance, despite an increase in training time for the same number of steps as the SSD model [15].

Doppler radars have a wide spectrum of applications, from high-end doppler guns used by police, to more cost-effective designs used for commercial applications [6]. For example, One automotive application utilizes the doppler radar as a complementary system for tachometers [7]. Similar to [2], [8] is a CW Doppler radar implementation that detects abnormal human movement, such as falling, but doesn't use a camera out of consideration for patient privacy. The CW Doppler radar in [9] had an implementation of a digitally controlled calibrator that can simulate moving targets within the 8-12 GHz frequency band, which is within the range of the HB100 radar used in this experiment.

CFAR is a commonly used algorithm to detect targets against a background of noise and clutter. However, there are a few different types of this algorithm that work better in specific scenarios, as shown by [10]. Building upon that, [11] improved upon the SOCA-CFAR algorithm that aimed to alleviate masking effects from multiple targets mixed with a large target.

C. Equipment

In the signal processing domain, the transceivers are the most essential components for detecting human presence. The two components used for this experiment are the HB100 and the CDM324 transceivers. Both of these transceivers lie within the same price range of 10 USD.

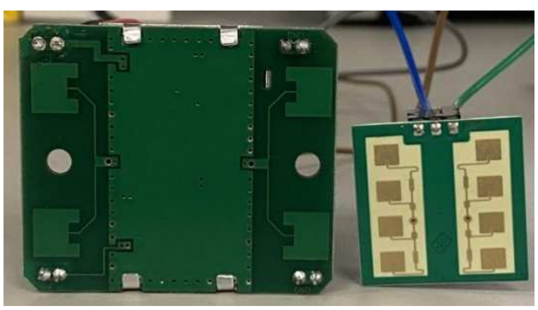

Fig. 1. HB100 (left) and CDM324 (right) transceivers side by side

The HB100 is a transceiver that operates in the X-band frequency of 10.525 GHz with an antenna beamwidth of 80 degrees for the azimuth angle and 40 degrees for the elevation angle. The HB100 is designed with 2 pairs of transmitting and receiving antennas. Conversely, the CDM324 operates in the K-band frequency of 24.125 GHz with an antenna pattern of 80 degrees for the azimuth angle and 32 degrees in the vertical angle. Unlike the HB100, the CDM324 is equipped with 4 pairs of transmitting and receiving antennas.

Since the Intermediate Frequency output signal is relatively weak, a suitable circuit is needed to amplify the signal and filter out the high frequency noise signal. Figure 2 shows the circuit setup using the LM358P operational amplifier interfaced with the HB100 transceiver. The HB100 was tested using a DC power supply and an Oscilloscope to measure the change in frequency.

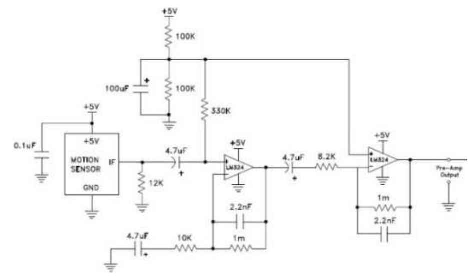

Fig. 2. Amplifier Circuit [12]

After passing the Intermediate Frequency signal through the amplifier circuit, the pre-amp output is connected to the Arduino to calculate the target's velocity using the doppler equation:

$$F_d = 2V\left(\frac{F_c}{c}\right)Cos\theta$$

Since the Raspberry Pi is not suitable for real-time systems, the Raspberry Pi is meant to offset the overhead by becoming the broker for the Signal Processing analysis between the analog and digital domains of the radar system.

The Raspberry Pi 4 desktop kit acts as the main computing interface that interacts with the processed data from the transceiver and the *LC26-1-US* camera. These components all work in conjunction for the purpose of performing the real-time object detection and tracking task.

II. IMPLEMENTATION

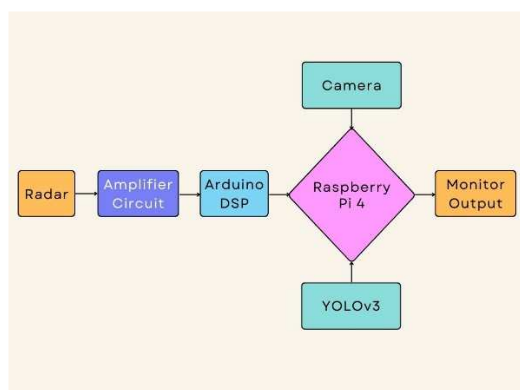

Fig. 3. Radar System Flowchart

A. Radar System Tracking

The Radar system consists of 7 main components; the transceiver, the amplifier circuit, the Arduino, the Raspberry Pi 4, camera module, object detection and tracking algorithm, and the monitor to display the output. The tracking algorithm utilizes digital signal processing techniques and a Computer Vision interface such as: establishing a serial communication between the Arduino and the Raspberry Pi, utilizing the Constant False

Alarm Rate algorithm to record the velocity movement of the current target [10], and employing the Computer Vision model to detect, track, and display the target's qualitative characteristics on the monitor in a real-time setting [2].

B. Constant False Alarm Rate (CFAR)

The Constant False Alarm Rate algorithm is a cell-averaging algorithm that uses a threshold to detect peaks from the signal input. The CFAR algorithm consists of a Cell Under Test, Guard Cells to avoid estimated corruption, training cells, and a threshold level to detect peaks and stay above the noise level. This method comes into play as a way to analyze the target's history of movement and presence. It's also used to distinguish a target's presence in the antenna beam detection zone and simply natural interference [10].

Figure 4 Shown below demonstrates an example of how the peak detection algorithm works when conducted over the span of a timed interval.

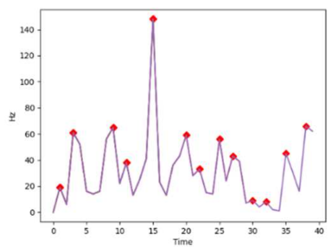

Fig. 4. CFAR Peak Detection

C. YOLOv3 Model

As mentioned before, two different YOLOv3 models are taken into consideration for the sake of finding the optimal setup. In short, the YOLOv3-608 model is preferred for use-cases that prefer high confidence levels, while the YOLOv3-tiny model is best used for scenarios where speed and minimal system latency is preferred [14]. For this real-time system, the confidence levels are averages over the duration of a trial that are discussed in the next section. The purpose for this is to take into consideration the accuracy with respect to a live feed as opposed to a still image and see how the tradeoff plays out.

III. Experiment

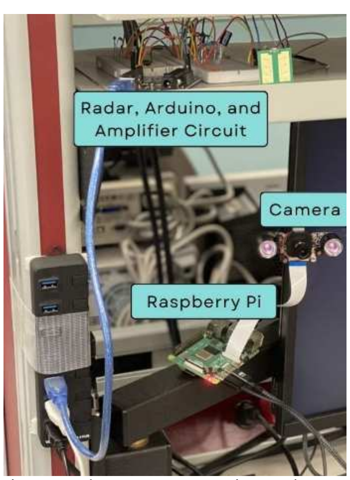

Fig. 5. Radar System Experimental Setup

Figure 5 Shown above demonstrates how the radar system was set up to collect data from the target's movement with respect to the trial run. The trials are set up to test the performance of our radar system with respect to different tracking scenarios. These scenarios include; walking from left to right, walking right to left, walking towards the camera, and walking away from the camera. The last two trials combine each of the last two scenarios to consider a full round trip scenario where a person returns to their starting point of the trip. The intention of these trials are to test common tracking scenarios that the system will be implemented in a realistic scenario.

After running tests from our last trial, the next goal is to add a sensitivity threshold to ignore signals below the defined threshold. The threshold is also set to ignore extreme values that can be acquired from nearby equipment which includes; routers, models, desktop computers, and other electronic equipment that emit radio waves. While the CFAR is meant to analyze the person's movement during the trial experiments, the frequency threshold is meant control the camera so it can ignore values below the set threshold. The radar transceiver chosen for the frequency threshold tests depends on the results from Table I and Table II.

Fig. 6. Example of a trial run in the real-time setting

Figure 6 Shown above displays the output from the radar system captured on the monitor's real-time feed, which continuously updates the confidence level from the Computer Vision algorithm and the velocity from the radar, measured in miles per hour, (MPH). In this example, the YOLOv3-tiny model predicted a human within the bounding box with a 67% accuracy while clocking the target's speed at 3.41 MPH [5].

IV. Results

Table I. YOLOv3-tiny trial results

Trial	*CDM324 System Latency (seconds)*	*CDM324 Average Classification Accuracy*	*HB100 System Latency (seconds)*	*HB100 Average Classification Accuracy*
1	7.0433	88.13%	6.6681	83.07%
2	6.2876	81.82%	6.2676	77.63%
3	9.1412	72.86%	7.0745	67.47%
4	8.2585	63.75%	6.6284	58.41%
5	10.3527	79.76%	10.1699	83.32%
6	12.6195	82.74%	13.9123	81.24%
Average Total	8.95	78.18%	8.45	75.19%

The results from Table I and Table II showcase the results based on each of the trials mentioned from the previous section. The metrics that are calculated based on the trials include the System latency and Average classification accuracy with respect to the transceiver and the YOLOv3 model under test. System latency is defined as the time it takes detect the target's presence and process a bounding box in the monitor's real-time feed. Furthermore, the Average classification accuracy is defined as the averaged confidence within the bounding box over the span of the current trial.

To get a grasp on the radar system's performance over the various trials, the average total is the final metric that's used to provide a reliable source for deciding on the set up that provides the optimal radar system.

TABLE II. YOLOV3-608 TRIAL RESULTS

Trial	*CDM324 System Latency (seconds)*	*CDM324 Average Classification Accuracy*	*HB100 System Latency (seconds)*	*HB100 Average Classification Accuracy*
1	12.6781	99.34%	17.0774	77.46%
2	12.5845	97.95%	12.7958	66.27%
3	12.9489	99.62%	12.7611	86.85%
4	12.6638	99.76%	12.7735	87.73%
5	16.2596	98.87%	12.8177	78.42%
6	19.7852	85.05%	16.57	87.97%
Average Total	14.4867	96.77%	14.1326	80.76%

Based on the results from Table I and Table II, the best setup chosen for the threshold test is the combination of the CDM324 and the YOLOv3-tiny model. The CDM324 is chosen over the HB100 is due to the higher operating frequency of 24 GHz, which makes it more sensitive to detecting a target's presence. The only trade-off being that it becomes prone to detecting interference from the surrounding electrical equipment. Although the HB100 is shown to be slightly faster on average, based on the results from Table I and Table II, the CDM324 outperforms the former in every table with the Average classification accuracy metric. Despite sacrificing a couple tenths of a second, the CDM324 provides superior accuracy regardless of the chosen YOLOv3 model as every table shows in the Average Total metric.

TABLE III. YOLOV3-TINY SERIAL THRESHOLDING TEST

Threshold (Hz)	*CDM324 Average Classification Accuracy*	*HB100 Average Classification Accuracy*
5	64.43%	67.69%
10	94.64%	78.01%
15	97.98%	94.57%
20	87.14%	96.90%
Average Total	86.05%	84.29%

Table III and Table IV focus on measuring the Average classification accuracy with respect to the frequency threshold measured from the transceiver with respect to the differing YOLOv3 models. Just like the previous trial tests, the CDM324 transceiver outperformed its HB100 by a slight margin.

TABLE IV. YOLOV3-608 SERIAL THRESHOLDING TEST

Threshold (Hz)	*HB100 Average Classification Accuracy*	*CDM324 Average Classification Accuracy*
5	85.43%	81.85%
10	76.58%	76.85%
15	78.99%	75.85%
20	78.53%	77.20%
Average Total	79.88%	77.94%

V. CONCLUSION

An examination of the results above conclude that the most efficient radar system for this study was powered by a CDM324 transceiver coupled with the YOLOv3-tiny Computer Vision model. These two chosen components provide the optimal tradeoff of speed and efficiency as demonstrated through two main experiments. While the system latency is negligible for both tested transceivers, the notable differences in performance is displayed when comparing the averaged total for the average classification accuracy regardless of the YOLOv3 model chosen. Since the YOLOv3-tiny model provides us the final latency with at least a six second difference, it serves as the preferred option compared to its YOLOv3-608 counterpart.

FUTURE WORK

This work will continue by creating a radar system that incorporates high-end RF components along with Signal Processing principles to create a Synthetic Aperture Radar that utilizes coffee-can antennas to propagate and receive a signal operating in the 2.4 GHz ISM band. The new system will also incorporate a Computer Vision interface to classify the target.

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