

Indoor Human Activity Detection System Based on Millimeter-Wave Radar

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Abstract: Millimeter-wave radar has strong application value in industrial sensing and intelligent monitoring, while indoor personnel detection based on visual sensors may introduce privacy risks and can be affected by illumination and occlusion. On the basis of the original FMCW millimeter-wave radar scheme, this paper condenses the system design and experimental verification of an indoor personnel detection system using the IWR6843/IWR6843AOP radar platform. The study keeps the radar signal-processing chain, including point-cloud generation, static clutter cancellation, CA-CFAR detection, Capon direction-of-arrival estimation, DBSCAN clustering, and Kalman or extended Kalman tracking. A Python upper-computer platform integrates serial communication, radar parameter configuration, multithreaded data parsing, OpenCV visualization, Tkinter control, and Flask Web monitoring. Indoor tests show that the system can detect, count, locate, and track moving personnel in a 3 m×4 m room, and that target point-cloud density changes with range. The results also indicate that tracking accuracy decreases when multiple targets are close to each other or remain static, which provides a clear direction for improving filtering and tracking performance.

Keywords: Millimeter-wave radar, FMCW, IWR6843AOP, point-cloud imaging, indoor personnel detection, DBSCAN, Kalman tracking.

1. Introduction

Human activity recognition and indoor personnel sensing are widely used in intelligent buildings, security monitoring, and health-related environments. Conventional camera-based methods provide rich visual information, but they rely on illumination, may fail under occlusion, and can expose private information. Millimeter-wave radar operates in the 30-300

GHz frequency band with millimeter-level wavelength, and it can estimate target range, velocity, and angle under weak light, smoke, and non-contact conditions. The technology is therefore suitable for indoor personnel detection, counting, localization, and tracking. Recent studies have also shown that millimeter-wave radar can support communication, imaging, short-range sensing, human activity recognition, gait feature estimation, posture monitoring, and multi-object tracking [1-2].

Table 1. Sensor Performance Comparison

Item	Millimeter-wave radar	LiDAR	Camera	Ultrasonic	Infrared
Long-range ability	Excellent	Excellent	General	Poor	Good
Resolution	High	High	High	Low	Low
False-alarm rate	Low	Relatively low	Relatively low	Relatively low	High
Temperature adaptability	Excellent	Excellent	Excellent	General	Good
Darkness adaptability	Excellent	Excellent	General	Excellent	Excellent
Weather adaptability	Excellent	General	General	General	General
Dust and humidity	Excellent	General	General	Good	General
Hardware cost	Low	High	Low	Low	Low
Signal-processing complexity	Low	High	High	Low	Low

The original study compares millimeter-wave radar with LiDAR, cameras, ultrasonic sensors, and infrared sensors, and emphasizes the radar advantages of long-distance capability, high resolution, low false-alarm rate, strong adaptability to darkness, and relatively low hardware cost. Table 1 retains the sensor comparison from the source document and translates the entries into English.

This paper compresses the original work into an eight-page journal-style article. The retained technical line is: FMCW ranging, velocity measurement and angle measurement; point-cloud imaging and target detection; Capon DOA estimation, DBSCAN clustering and Kalman tracking; IWR6843AOP hardware; Python-based local and Web

visualization; and indoor experimental verification [3-6].

2. FMCW Millimeter-Wave Radar Principle

The source document uses FMCW radar as the basic ranging and sensing mechanism. The radar transmits a frequency-modulated continuous wave and obtains the intermediate-frequency beat signal by mixing the transmitted and received signals. Compared with a real mixer, the quadrature mixer generates a complex baseband signal, improves anti-interference ability, helps compensate phase and frequency offset, and makes subsequent digital

processing more convenient.

For a target at range R , the round-trip delay is expressed as

$$\tau = \frac{2R}{c} \quad (1)$$

Where c is the propagation velocity of the electromagnetic wave. The beat frequency generated by the FMCW waveform is

$$f_b = \frac{2BR}{cT_c} \quad (2)$$

And the target range can be obtained from

$$R = \frac{cT_c f_b}{2B} \quad (3)$$

The original derivation further shows that range resolution depends on the sweep bandwidth. When two targets can be distinguished in frequency, the range resolution is

$$R_{res} = \frac{c}{2B} \quad (4)$$

Velocity measurement is realized by observing the phase change of the same target across consecutive chirps. Under the simplified condition retained in the source document, the velocity can be expressed as

$$v = \frac{cf_\phi + B}{2f_0} \quad (5)$$

For angle measurement, two receiving antennas observe the same target with a phase difference caused by the path difference. When antenna spacing is d and wavelength is λ , the target angle is

$$\theta = \sin^{-1}\left(\frac{\lambda \Delta \phi}{2\pi d}\right) \quad (6)$$

These equations form the mathematical basis for range, velocity, and angle estimation. The final point-cloud image is obtained after static clutter filtering, CFAR detection, phase compensation, and DOA estimation.

3. Point-Cloud Detection, Clustering and Tracking

The original system forms a point cloud by converting detected radar targets into spatial coordinates. Static clutter cancellation is used to suppress environmental reflections, CA-CFAR provides adaptive target detection, and non-coherent accumulation and peak grouping improve the target extraction quality. Direction-of-arrival estimation is then used to recover angular information. The source compares FFT, conventional beamforming, Capon and MUSIC methods. The simulation condition uses 3 transmitting antennas, 4 receiving antennas, half-wavelength spacing, a 60 GHz center frequency, 512 snapshots, 20 dB SNR, and two targets at 20°

and 45°. The original conclusion is that FFT has the poorest angular resolution, conventional beamforming is slightly better, Capon has smaller error, and MUSIC has the best resolution but higher complexity. Therefore, Capon is selected in the implemented system [7-9].

The point-cloud coordinate relation retained from the source is

$$\Delta x = R \cdot \cos(\varphi) \cdot \sin(\theta), \Delta y = R \cdot \cos(\varphi) \cdot \cos(\theta), \Delta z = R \cdot \sin(\varphi) \quad (7)$$

Because the coordinates depend on range, the point spacing becomes smaller when the target is closer to the radar, and the corresponding point cloud is denser. Angular resolution is mainly affected by the antenna number and antenna aperture, so more transmit and receive channels can improve point-cloud imaging quality.

After the point cloud is generated, clustering associates the detected points with physical targets. The source describes K-means and DBSCAN and finally emphasizes DBSCAN because it can identify arbitrary-shaped clusters and treat noise points separately. In the radar point-cloud scene, DBSCAN groups dense points into a target cluster and uses the centroid of the cluster as the target position. This is suitable for moving human targets in indoor scenes, where the number and shape of target clusters are not fixed.

For tracking, the source uses Kalman filtering and extended Kalman filtering. Each detected object can be assigned a separate filter, while clustering and data association determine whether the filter receives reliable observations. The standard linear state and observation equations are

$$\mathbf{x}_t = \mathbf{A}\mathbf{x}_{t-1} + \mathbf{B}\mathbf{u}_t + \mathbf{s}_t, \mathbf{z}_t = \mathbf{C}\mathbf{x}_t + \mathbf{v}_t \quad (8)$$

Where $\mathbf{A}$ is the state transition matrix, $\mathbf{B}$ is the control matrix, $\mathbf{C}$ is the observation matrix, $\mathbf{s}_t$ is state-transition noise, and $\mathbf{v}_t$ is observation noise. For nonlinear tracking, the extended Kalman filter linearizes the system by Taylor expansion and uses Jacobian matrices for prediction and update, which is closer to practical indoor personnel tracking [10].

4. System Design and Hardware Platform

The indoor personnel detection system is built around the IWR6843/IWR6843AOP millimeter-wave radar platform. The system completes FMCW signal transmission and reception, filters and processes the received signal, sends the processed point-cloud data to the upper computer through serial communication, and performs clustering, tracking, counting, and visualization. Figure 1 uses the original embedded figure extracted directly from the PDF and summarizes the system functional modules.

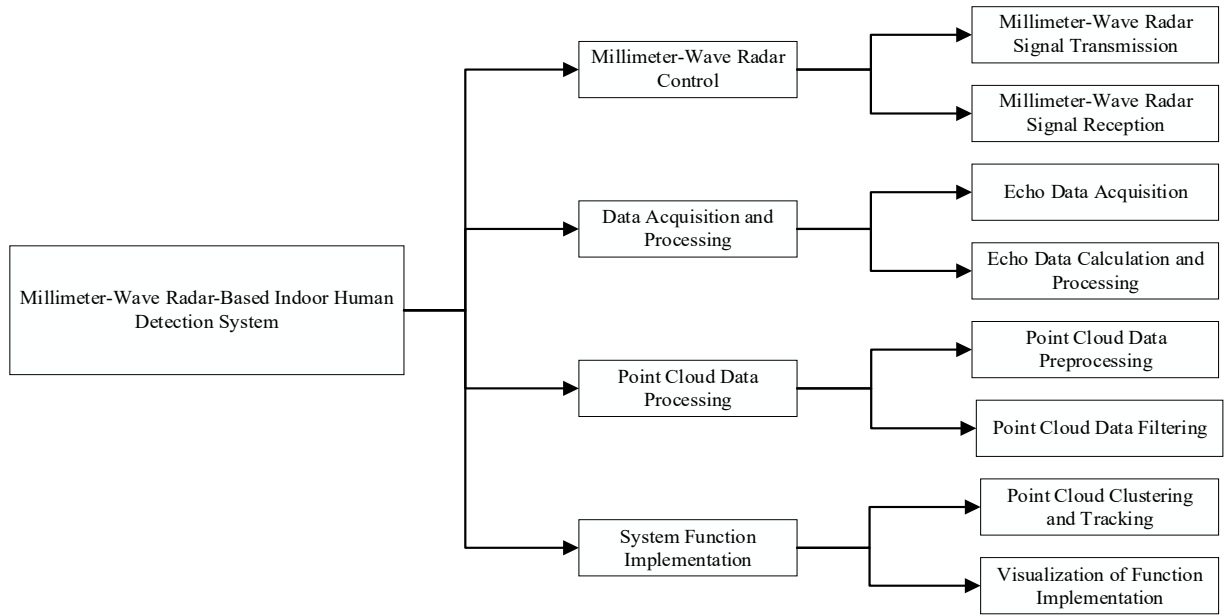


Figure 1. System Functional Module Diagram

The system is divided into four modules: radar control, data acquisition and processing, point-cloud data processing, and functional visualization. Radar control completes front-end configuration and signal transmission/reception. Data acquisition and processing calculate relative distance and velocity. Point-cloud processing includes static clutter filtering, non-coherent accumulation, CFAR detection, peak grouping, Doppler phase compensation and DOA estimation. The functional module performs clustering, tracking, counting, and visual output.

The source chooses IWR6843 as the 60 GHz radar RF front end and digital radar signal-processing platform. It integrates a fast FMCW front end, an Arm Cortex-R4F MCU and a TI C674x DSP. Its main characteristics are translated in Table 2.

The IWR6843AOPEVM module includes two micro-USB interfaces, CAN and I2C interfaces, a millimeter-wave radar sensor, a control part, and a DSP part for radar data processing. The board can communicate through configuration and data serial ports. The selected design reads the processed radar data from the serial port rather than directly reading raw ADC data, because the on-chip processor already provides a complete processing chain.

Figure 2 presents the IWR6843 functional block diagram and clarifies the radar front-end, digital processing, and interface modules used by the platform.

Table 2. Main Characteristics of IWR6843

Parameter	Description
FMCW transceiver	Integrated PLL, transmitter, receiver, baseband and ADC, with built-in calibration and self-test
RF bandwidth	60 GHz to 64 GHz coverage with 4 GHz continuous bandwidth
Receiving channels	4
Transmitting channels	3
Phase shifter	6-bit phase shifter supporting TX beamforming
Chirp engine	Ultra-precise chirp engine based on fractional-N PLL
TX power	12 dBm
RX noise figure	12 dB
Processor	C674x DSP and ARM-R4F microcontroller supporting autonomous mode
Interfaces	6 ADC channels, 2 SPI ports, 2 UARTs, 1 CAN-FD, I2C and GPIO
Clock source	40 MHz crystal oscillator
Operating condition	Junction temperature from -40°C to 105°C

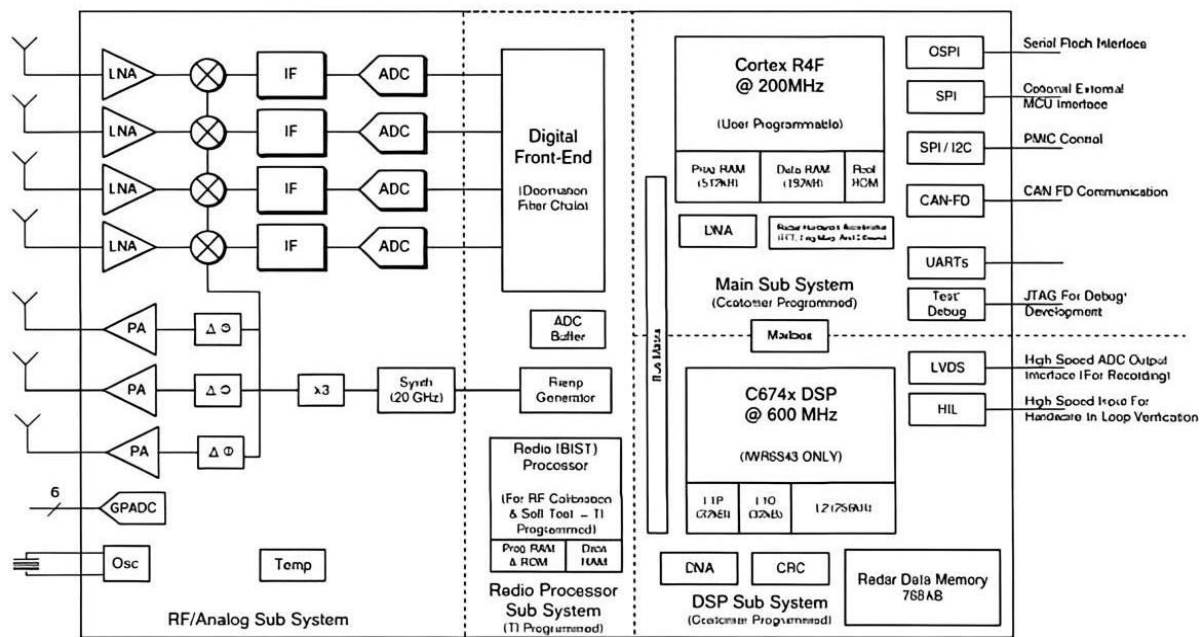


Figure 2. IWR6843 Functional Block Diagram

5. Python Upper-Computer Software

The upper-computer system is developed in Python and integrates serial communication, radar parameter configuration, data parsing, coordinate calibration, visualization, and Web monitoring. It receives personnel detection data from the IWR6843AOP radar in real time, parses target coordinates, counts people, draws trajectories, and pushes monitoring information remotely.

The software uses global variables to manage cross-thread

data sharing. Data variables store the current frame, current number of people, historical number of people and the list of current targets. Control variables manage pause, termination, and serial-port status. Hardware variables manage the serial object and camera object. This design allows all threads to obtain the current system status and monitoring data in real time.

Table 3 Summarizes the core global variables used for cross-thread data sharing, control-state management, and radar/camera hardware access.

Table 3. Core Global Variables

Type	Variable	Data type	Function
Data	Frame	int	Stores the current radar frame number
Data	Now_People	int	Stores the current number of detected human targets
Data	History_People	int	Stores the historical total number of detected human targets
Data	Now_People_List	list	Stores target ID, 3D coordinates and 3D velocities
Control	pause_all_flag	int	Pause flag: 0 for normal operation and 1 for pause
Control	kill_all_flag	int	Termination flag: 0 for normal operation and 1 for termination
Control	com_close_flag	int	Serial-port close flag: 0 for open and 1 for closed
Hardware	COMM	serial.Serial	Serial object for radar communication
Hardware	cv2_cap	cv2.VideoCapture	Camera object for video-frame acquisition

Hardware initialization includes network detection, camera self-adaptive initialization, and radar CLI command design. Network detection obtains the local IP address by trying to connect to public DNS. Camera initialization scans devices numbered from 0 to 4 under `cv2.CAP_DSHOW` mode and stores the first available camera object. The radar configuration commands standardize the working mode and support stable human-target data acquisition.

Serial communication adopts a two-thread design. The receiving thread reads the serial buffer, waits briefly to ensure a complete frame, concatenates the data frame, converts it to

string format, and sets the reception-complete flag. The parsing thread listens to the flag, extracts frame number, target number, target ID, three-dimensional coordinates, three-dimensional velocity and historical count, then updates the global variables. Exception capture is included to prevent system crash caused by abnormal data format.

Figure 3 illustrates the two-thread serial communication workflow, while Figure 4 shows the cropped radar-control interface used for local parameter configuration and monitoring.

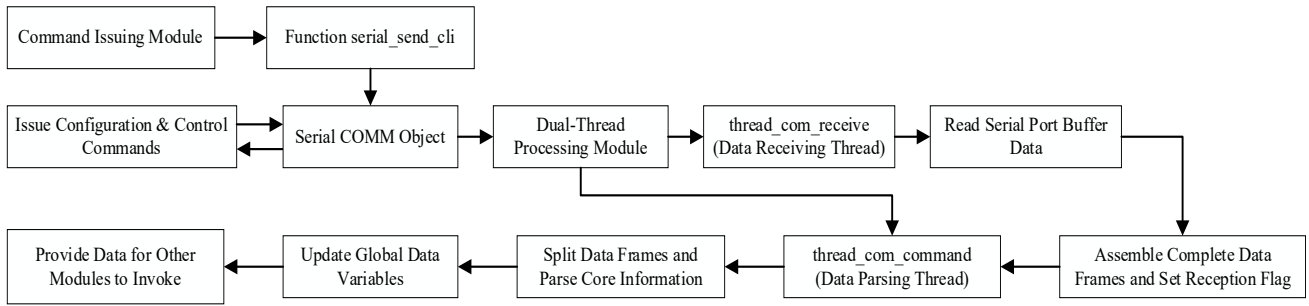


Figure 3. Serial Communication Flowchart

The visualization module combines camera video and radar data. The camera part displays local video and provides an HTTP video stream through the /video_feed interface. The radar part loads the monitoring-region background and maps target coordinates to image pixels, draws rectangles, labels target ID, height and speed, and displays frame number, current number of people and historical number of people.

The local Tkinter GUI supports serial scanning, baud-rate selection, radar startup and shutdown, default and customized parameter configuration, pause and resume. The Flask Web service binds to 0.0.0.0 and allows devices in the local network to access the current monitoring data and video streams.



Figure 4. Serial Communication and Radar-Control Interface

6. Indoor Test and Result Analysis

The test environment in the source document is Room 507 of Dongfang Apartment, with a 3m×4 m area. The IWR6843 radar has 3 transmitting antennas and 4 receiving antennas, generating 12 virtual antennas aligned on the PCB. More antennas along the X axis improve azimuth resolution, while more antennas along the Y axis improve elevation resolution. The source states that, depending on height and room size, an installation height below 2.5m and a boresight angle below 20° relative to the horizontal plane can satisfy the indoor detection requirement.

Figure 5 replaces the original personnel photograph with a non-identifying schematic of the indoor test-room layout and radar observation arrangement.

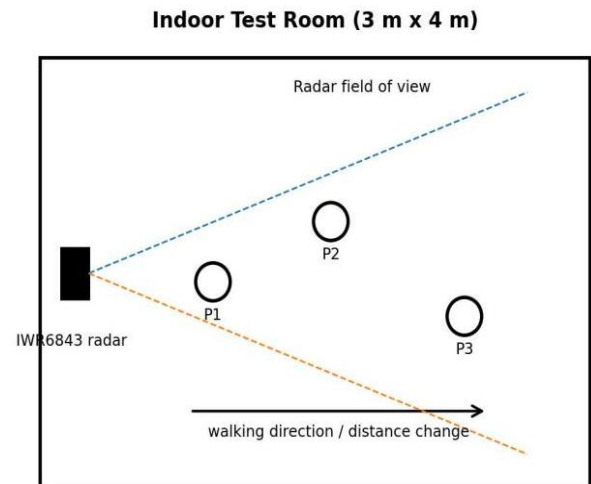


Figure 5. Indoor Test-Room Layout and Radar Installation Schematic

The source performs multi-scenario tests to verify whether the system can achieve the expected functions. In the point-cloud clustering test, the tester moves away from the radar. The results show that the point cloud can basically describe moving objects in the scene and that the clustering effect is good. When the tester is closer to the radar, the point cloud is denser; when the tester is farther away, the point cloud

becomes relatively sparse. When multiple targets are present, tracker performance becomes worse because relative movement between people introduces more complex point-cloud patterns.

Figure 6 shows the radar point-cloud result when personnel move away from the radar, demonstrating the relationship between target distance and point-cloud density.

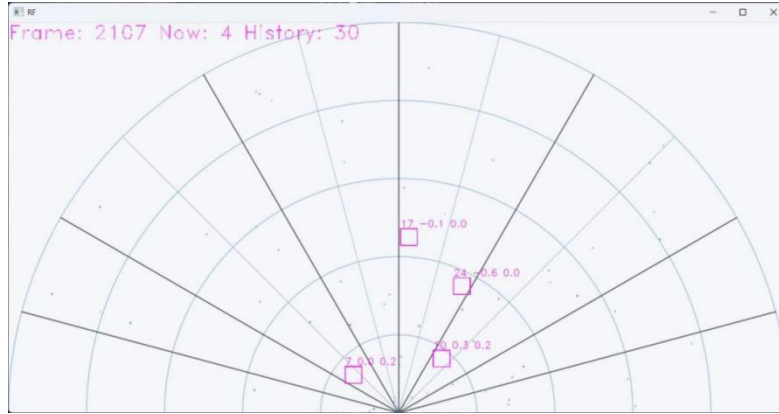


Figure 6. Radar Test Result for Personnel Moving Away from the Radar

The source also tests posture recognition. The criterion is the target height obtained by tracking the same person, and the standing and sitting states are distinguished by the height variation. The results show that posture can be judged from the height change of the same target, and target position can be identified from the spatial position of the point cloud. For moving objects, the system performs well. Static clutter filtering removes most noise points produced by non-human objects, so each target appears as a separate isolated cluster. When more targets are added and the targets are close to each

other, tracking accuracy gradually decreases because point-cloud complexity increases. When many people remain seated, tracker performance also becomes poor because static targets affect system judgment. The source therefore suggests improving tracking performance and point-cloud filtering to enhance accuracy.

Figure 7 shows the radar result used for standing and sitting posture recognition, where the tracked height variation supports state judgment.

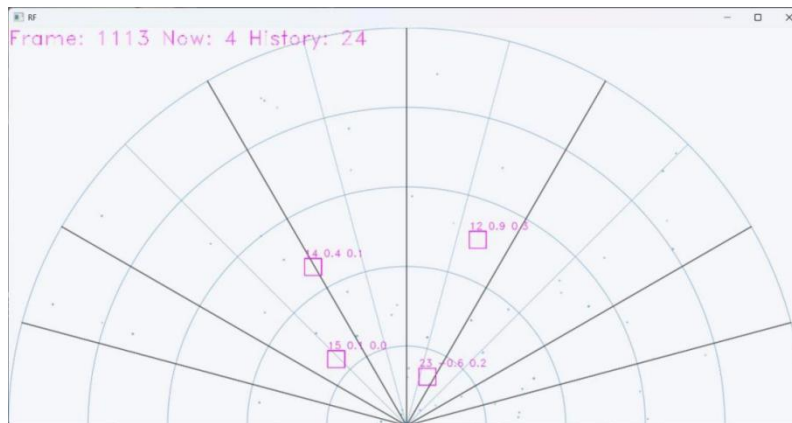


Figure 7. Radar Test Result for Standing and Sitting Posture

7. Conclusion

This paper condenses the original study of an indoor personnel detection system based on FMCW millimeter-wave radar. The retained system uses IWR6843/IWR6843AOP as the sensing and processing platform, implements a radar point-cloud processing chain including clutter filtering, CFAR detection, Capon DOA estimation, DBSCAN clustering and Kalman tracking, and designs a Python upper-computer system with serial communication, radar configuration, local GUI, camera-assisted visualization and Flask Web monitoring. The experimental results in a 3 m × 4 m indoor environment show that the system can detect, count, locate and track moving personnel. The point-cloud density changes with target range, posture can be inferred from height variation, and the system has good performance for moving

objects. The source also identifies limitations: tracking accuracy decreases when multiple targets are close or static, and future improvement should focus on stronger tracking, better point-cloud filtering and more robust multi-target judgment.

Future research should expand the experiment to larger multi-room scenes, compare different radar installation heights and viewpoints, optimize multi-target association for close or static personnel, and evaluate long-term deployment stability.

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