

RESEARCH ON MODELLING AN AUTOMATED DISTANCE MEASUREMENT AND VISUALISATION SYSTEM BASED ON FREQUENCY-MODULATED CONTINUOUS WAVE

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Abstract

To realise high-precision, real-time, and automated distance measurement in frequency-modulated continuous wave systems, this study proposes a closed-loop ranging architecture that integrates signal modelling, error compensation, and visualisation feedback. The system constructs a chirp-based transmitter and a coherent receiver front-end, forming a complete signal chain encompassing frequency mixing, sampling, and spectral analysis. A multi-module simulation framework is implemented to derive accurate beat frequency–distance mappings using fast Fourier transform (FFT) extraction and least-squares fitting. To mitigate non-idealities, such as phase drift and sampling jitter, a phase error correction algorithm and adaptive bandwidth tuning mechanism are introduced, ensuring stable response across varying target scenarios. The software platform features a modular structure supporting real-time waveform monitoring, spectral trend tracking, and system parameter adjustment. Experimental validation across a 0.5–10 m range demonstrates an average distance error within ± 0.6 mm and a response latency below 150 ms, confirming the system's effectiveness under controlled disturbance environments. The proposed architecture provides a scalable foundation for intelligent sensing and automated ranging in robotics and embedded perception applications.

Key Words

Frequency-modulated continuous wave (FMCW), automated ranging system, system modelling, signal processing, visual control

1. Introduction

Recent advancements in intelligent manufacturing, mobile robotics, and autonomous navigation systems have imposed increasingly demanding requirements on distance measurement technologies, including sub-millimeter precision, low-latency response, and robust real-time performance. Traditional ranging methods based on pulsed lasers or ultrasonic waves are susceptible to noise coupling, material-dependent propagation variations, and multipath interferences, resulting in reduced signal-to-noise ratio (SNR) and unstable distance estimates—especially under dynamic and constrained sensing environments. These challenges hinder their integration into modern sensor modules that require compact size, continuous operation, and high accuracy.

Frequency-modulated continuous wave (FMCW) radar has emerged as a preferred solution for real-time, high-resolution ranging. By leveraging linear frequency modulation (LFM), FMCW radar encodes target distance into beat frequency differences between transmitted and received signals. This technique enables precise multi-target detection with millimeter-level resolution, even under limited bandwidth conditions, and thus plays a central role in robotics perception and automated sensing systems.

Despite its theoretical maturity, FMCW-based ranging systems still face significant implementation bottlenecks. Practical deployments are often challenged by the hardware-induced model deviations, non-ideal mixing stages, accumulated phase noise, and insufficient link-level error suppression. Existing compensation techniques tend to focus on single-stage correction—such as phase alignment

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or frequency linearisation—but fail to consider system-wide error propagation across the modulation–mixing–sampling chain. Moreover, the lack of integrated modelling frameworks prevents accurate evaluation and suppression of such errors under closed-loop operation.

To address these issues, this paper proposes a system-level modelling and full-chain error compensation strategy for FMCW automated ranging systems. The main contributions are as follows.

- (1) A complete modelling framework is established, covering key stages from LFM signal generation to beat frequency demodulation, allowing detailed analysis of spectral peak drift, parameter perturbation, and resolution loss [1].
- (2) A hybrid distance estimation algorithm is designed, combining FFT-based frequency extraction with phase compensation using least-squares fitting and Hilbert transform to enhance distance calculation stability under dynamic link variations.
- (3) A modular processing architecture is developed, integrating signal generation, compensation control, and real-time visualisation into a feedback-driven closed-loop system, which significantly improves system robustness and engineering scalability in intelligent robotic applications.

2. Related Work

Recent studies on FMCW radar systems have extensively explored signal processing architectures, compensation models, and implementation frameworks tailored to real-time distance measurement scenarios. Qin *et al.* [2] designed a low-cost FMCW radar platform with integrated distance and angle estimation modules, achieving sub-centimeter accuracy through enhanced beat frequency demodulation strategies. Duan *et al.* [3] proposed a calibration algorithm that corrects system delay and frequency offset in real-time, improving ranging accuracy and reliability in embedded FMCW systems. Fan *et al.* [4] developed a spectral feature extraction framework incorporating frequency bin interpolation and phase correction, which significantly improved target localisation resolution across varying distances.

Domuta and Palade [5] introduced a two-way clock compensation method for asynchronous systems, improving time-of-flight accuracy under clock deviation conditions. Park *et al.* [6] proposed an external feedback compensation mechanism for high-resolution mobile displays, offering useful insights into dynamic error suppression strategies applicable to radar synchronisation chains. In parallel, research on signal denoising and spectral enhancement has also gained momentum. For example, Bond-Taylor *et al.* [7] comparatively reviewed generative modelling techniques, such as VAEs and GANs, which, although not radar-specific, offer promising directions for spectral enhancement under weak signal conditions.

In terms of implementation robustness, Kumar and Sharma [8] emphasised the importance of quality-of-service frameworks for sensor networks in robotic systems, while

Cai *et al.* [9] demonstrated the utility of structured-light-based visual sensing in high-noise manufacturing environments. These diverse yet complementary efforts reflect the growing trend toward integrating FMCW radar with high-performance computing, compensation control, and modular signal architectures in both robotic perception and real-time measurement contexts.

3. Principles of Frequency-Modulated Continuous Wave Ranging and System Modelling

3.1 Mathematical Model of FMCW Signals

FMCW radar estimates target distance by transmitting an LFM chirp and coherently mixing it with the delayed echo. To establish an analytically tractable system formulation, the transmit signal, received echo, and beat-frequency generation process are explicitly modelled. Let the modulation slope be defined as

$$\mu = \frac{B}{T} \text{ (Hz/s)} \quad (1)$$

where B is the sweep bandwidth, and T is the modulation period. The transmitted chirp signal is expressed as

$$s_t(t) = A_t \cos \left[2\pi \left(f_c t + \frac{S}{2} t^2 \right) \right] \quad (2)$$

$$s_r(t) = A_r \cos \left[2\pi \left(f_c (t - \tau) + \frac{S}{2} (t - \tau)^2 \right) \right] \quad (3)$$

where $s_t(t)$ is the transmitted signal, $s_r(t)$ is the echo signal, f_c denotes the signal center frequency (GHz), $S = B/T$ represents the LFM slope (MHz/ μ s), $\tau = 2R/c$ indicates the signal round-trip delay time, R signifies the target distance, $c \approx 3 \times 10^8$ m/s is the speed of light, and A_t and A_r denote the signal amplitudes.

The mixer processes the product of the local transmit signal and the received signal to generate a beat frequency signal

$$s_b(t) = s_t(t) \times s_r(t) \approx \cos [2\pi f_b t + \phi(t)] \quad (4)$$

where the beat frequency $f_b = S\tau = \frac{2SR}{c}$ is a direct function of target distance, and $\phi(t)$ represents the phase residual term. This relationship forms the core formula for FMCW radar distance estimation, with its analytical distance expression given by

$$R = \frac{c \times f_b}{2S} \quad (5)$$

The accuracy of the above model is constrained by frequency modulation linearity, sampling delay, and phase error. Therefore, a phase compensation mechanism will be introduced in subsequent sections to enhance robustness [10]. System modelling and simulation parameter configurations are detailed in Table 1, reflecting the ranging performance achieved in a typical 77-GHz millimeter-wave FMCW system with a 500-MHz bandwidth, 1-ms modulation period, and 10-Msps sampling rate. The theoretical distance resolution reaches 0.3 m, supporting a maximum ranging range of 10 m.

Table 1
FMCW Signal Modelling and Parameter Configuration

Parameter Name	Symbol	Value and Unit	Description
Center frequency	f_c	77 GHz	Carrier frequency, determining signal penetration, and spatial resolution capability
Modulation bandwidth	B	500 MHz	Frequency scan range, affecting the system's range resolution
Modulation period	T	1 ms	Time period per sweep
Scan slope	S	0.5 MHz/ μ s	Frequency change rate, calculated as $S = B/T$
Sampling rate	f_s	10 Msps	Analog-to-digital conversion rate, affecting the precision of signal capture
Maximum range measurement	$R_{\max}$	10 m	Maximum achievable ranging capability of the system
Theoretical distance resolution	ΔR	0.3 m	Calculation formula: $\Delta R = c/(2B)$, which determines ranging accuracy

3.2 System Signal Flow Modelling

3.2.1 Modelling of Transmit and Receive Signal Chains

The transmit and receive links of FMCW radar form the core of ranging system modelling, where link model accuracy directly impacts beat frequency generation quality and subsequent distance estimation performance. As shown in Fig. 1, the system local oscillator (LO) generates a stable carrier with a center frequency of 77 GHz. This carrier is modulated by a triangular or sawtooth wave through an LFM module, producing a linear sweep signal with bandwidth B , period T , and slope $S = B/T$. Its time-domain expression is represented as

$$s_t(t) = A_t \cos\left(2\pi\left(f_c t + \frac{1}{2}St^2\right)\right) \quad (6)$$

where A_t is the transmitted signal amplitude and f_c is the carrier frequency. After amplification by the power amplifier (PA), the signal gains a gain factor GPA and is radiated by the transmit antenna with directional gain GTX. Target scattering introduces a propagation delay τ (proportional to distance). The echo signal, after free-space propagation loss, is received by the receive antenna (RX) and amplified by the low-noise amplifier (LNA) to suppress front-end noise. The received signal can be expressed as

$$s_r(t) = A_r \cos\left(2\pi\left(f_c(t - \tau) + \frac{1}{2}S(t - \tau)^2\right)\right) \quad (7)$$

The received signal and the transmitter's LO signal undergo difference mixing in the mixer to form a beat signal. The mixer output contains sum and difference frequency components. After filtering out high-frequency terms *via* a low-pass filter (LPF), only the difference frequency component is retained for calculation, whose frequency exhibits a linear correspondence with the target distance. This link model provides a foundational structure for incorporating subsequent non-ideal factors, such as PA nonlinearity, phase noise, and hardware mismatch,

enabling the establishment of a verifiable system-level modelling framework.

3.2.2 Simulation of Mixing and Sampling Processes

The mixing and sampling chain represents a critical modelling transition from the analog to digital domain in FMCW systems. Its modelling accuracy directly impacts beat frequency signal quality and distance calculation stability. The mixing output is constructed based on the product of the transmitted signal and the delayed echo signal, incorporating mixer non-idealities. The resulting beat frequency signal can be expressed as

$$s_b(t) = \alpha_m A_t A_r \cos(2\pi f_b t + \phi_m + \Delta\phi(t)) \quad (8)$$

where $s_b(t)$ is the beat frequency signal output from the mixer, A_t and A_r represent the amplitudes of the transmitted and received signals, respectively, f_b denotes the beat frequency, ϕ_m is the fixed phase offset introduced by the mixer, and $\Delta\phi(t)$ accounts for the dynamic phase error caused by frequency modulation. To suppress sum-frequency and image components, a fifth-order Butterworth LPF with an 800 kHz cutoff frequency is employed. The filtered signal is then digitised by the analog-to-digital converter (ADC). With sampling period T_s , the discrete-time representation becomes

$$s_b[k] = A_b \cos(2\pi f_b k T_s + \phi_0 + \phi[k]) + n[k] \quad (9)$$

This discrete formulation explicitly characterises the analog-to-digital transition and provides a unified mathematical interface for spectral analysis, phase compensation, and error suppression.

A mixed-signal simulation platform was implemented in MATLAB/SIMULINK. Figure 2 presents the time-domain waveform and frequency-domain response. After filtering, the beat peak attenuates by approximately 1.8 dB, while the noise floor increases by 2.3 dB. FFT analysis confirms a strictly linear relationship between beat frequency and distance, with a maximum deviation of ± 4.2 kHz, corresponding to a ranging error below ± 0.5 mm.

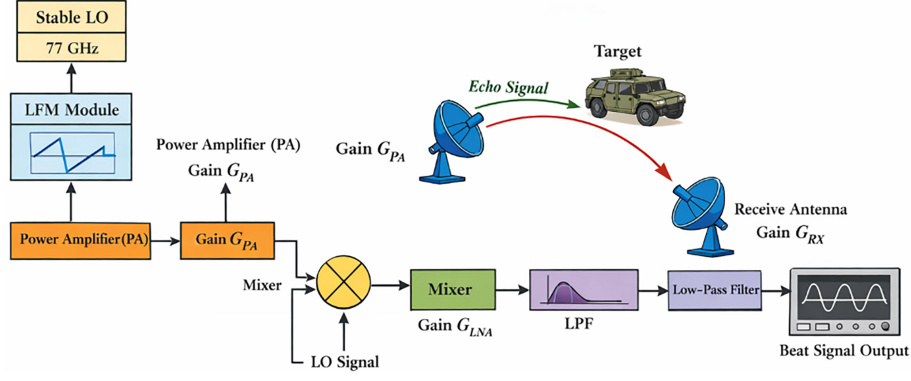


Figure 1. Schematic diagram of FMCW transmission and reception signal chain structure.

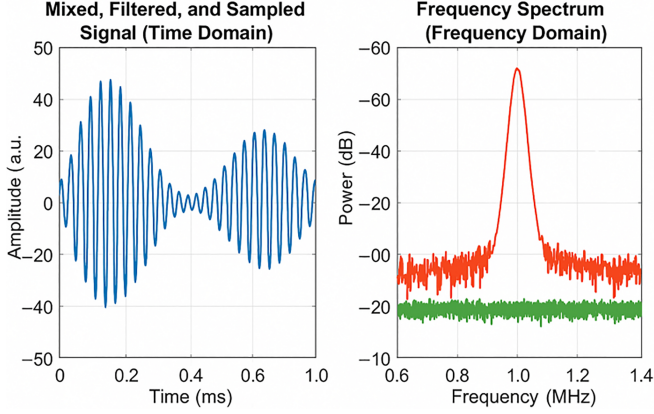


Figure 2. Time-domain and frequency-domain simulation results of mixing, filtering, and sampling processes.

These results validate the coupled effects of mixer nonlinearity, filter ripple, and sampling jitter, providing a theoretical foundation for subsequent compensation models.

3.2.3 System Modelling Parameters and Simulation Results Validation

To evaluate the internal consistency and engineering viability of the modelled FMCW radar signal processing chain, a complete multi-stage simulation environment was constructed using MATLAB/SIMULINK. The architecture comprises modules for linear frequency-modulated signal generation, echo modelling, analog mixing and filtering, non-ideal ADC sampling, and FFT-based spectrum extraction. Parameterised interfaces were defined for each module to support scalable configuration [11]. The simulated input signal was centered at 77 GHz with a bandwidth of 500 MHz and a modulation period of 1 ms, consistent with standard automotive FMCW radar specifications [12]. The ADC sampling rate was configured to 10 Msps, corresponding to a time-domain resolution of 100 ns.

Gaussian white noise and random phase perturbations were introduced to emulate hardware imperfections, such as thermal noise, LO drift, and power supply jitter, as highlighted in [13]. The signal chain was further subjected

to phase nonlinearity injection and filter ripple modelling to simulate practical component behaviour. Simulation outputs were transformed to the frequency domain *via* FFT for peak extraction and distance estimation. The root mean square error (RMSE) was used to assess accuracy across varying target distances, with the RMSE defined as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (R_m(i) - R_t(i))^2} \quad (10)$$

where $R_m(i)$ denotes the i th simulated ranging result, $R_t(i)$ represents the theoretical distance, and N indicates the number of samples. Results show that for a 0.5–10 m range, the simulation maintains an average distance error within ± 0.48 mm and an RMSE of 0.51 mm. The beat frequency spectrum peak demonstrates linear correlation with target distance, with maximum deviation limited to 4.2 kHz. Under all conditions, the SNR remains above 42.3 dB.

However, it is noted that these simulation results do not incorporate several real-world constraints. As discussed in [14], model fidelity can be undermined by unmodelled hardware imperfections, such as antenna gain non-uniformity, multipath reflections, and board-level cross-talk, which contribute significantly to experimental error. The practical system exhibited up to ± 2.9 cm error in long-range testing, indicating a $10\text{--}20\times$ deviation relative to simulation. This disparity underscores the importance of subsequent compensation models.

Sensitivity analysis was performed by varying phase noise amplitudes (0–0.05 rad), sampling jitter (± 3 ps), and filter cutoff ripple (up to 1.5 dB) [15]. Trends confirm stable simulation outputs under controlled deviations. Such parameter-tunable modelling approaches, as previously employed by Heo *et al.* [16] for FFT-based radar processing platforms, demonstrate the viability of modular system-level simulation prior to hardware deployment.

3.3 Error Source Analysis and Compensation Methods

In FMCW automated ranging systems, measurement accuracy is jointly affected by multiple error sources distributed across different stages of the signal chain.

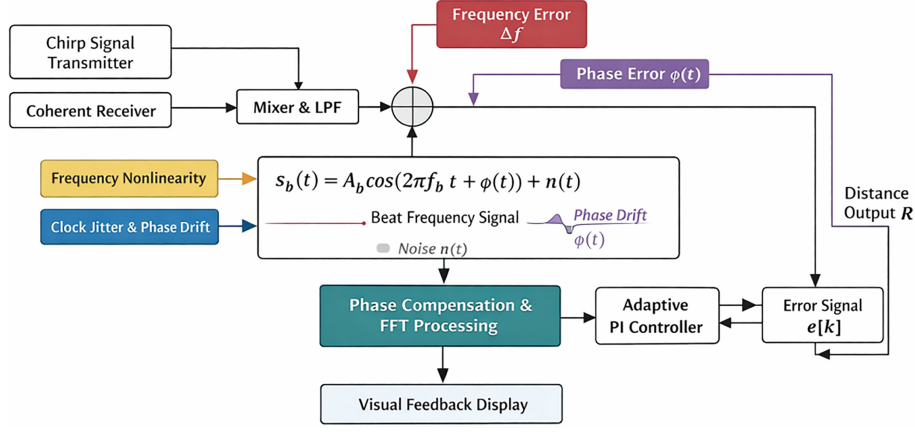


Figure 3. Structural diagram of error source modelling and compensation strategy for FMCW ranging system.

A systematic modelling of these error mechanisms is, therefore, essential for understanding their influence pathways and designing effective compensation strategies. The dominant error contributors can be categorised into frequency modulation nonlinearity, phase distortion in the radio-frequency mixing stage, clock-related timing deviation, link transmission delay, and temperature-induced parameter drift.

Frequency modulation nonlinearity arises when the instantaneous sweep of the transmitted signal deviates from an ideal linear relationship, leading to systematic bias in beat frequency extraction. Phase distortion is primarily associated with LO instability and mixer imbalance, which alters the periodicity and coherence of the beat signal. Clock-related errors, including sampling timing deviation and synchronisation mismatch, introduce time-of-flight uncertainty and directly affect distance estimation, as extensively analysed in clock compensation studies for ranging systems by Domuta and Palade. Environmental temperature variations further induce slow drift in circuit characteristics and effective propagation delay, accumulating over continuous operation.

To represent the combined influence of these heterogeneous error sources, an aggregated error propagation model is formulated in which the total ranging error is expressed as a weighted superposition of individual error terms, each scaled by its corresponding sensitivity coefficient. This formulation enables the separation of dominant contributors and provides a structured basis for compensation design.

Based on this modelling framework, a multi-level compensation strategy is constructed, with each module aligned to a specific segment of the signal chain. Frequency sweep correction targets modulation-stage nonlinearity, phase tracking compensates mixer-induced phase distortion, adaptive sampling adjustment mitigates clock-related timing deviation, and temperature-aware parameter adaptation suppresses slow environmental drift [17]. Such layered compensation architectures are consistent with system-level feedback correction principles reported in external compensation systems for high-resolution electronic platforms. As illustrated in Fig. 3, all compensation modules are implemented in parallel within

the SIMULINK environment, ensuring that error suppression spans the entire process from signal modulation to sampling demodulation in a coordinated manner.

4. Architecture and Visual Modelling Design of the Automated Ranging System

4.1 Hardware System Design

The hardware platform of the FMCW automated ranging system adopts a layered modular structure. Its core components include frequency-modulated signal generation, RF transmission and reception links, analog mixing and digital sampling structures, a system-wide clock synchronisation unit, and data communication modules. The overall architecture is shown in Fig. 4. The signal source is based on a digital direct synthesis (DDS) module, outputting a linear frequency-modulated signal centered at 77 GHz. The modulation slope is dynamically set by an FPGA controller, with linearity error controlled within $\pm 0.1\%$ to ensure stable frequency linearity of the beat frequency output.

The RF transmit chain incorporates a PA and a directional transmit antenna with 16 dBi gain, achieving a coverage angle better than $\pm 12^\circ$. The receive chain front-end incorporates an LNA with a noise figure below 2.1 dB, followed by a mirror-suppressed mixer for down-conversion with the LO signal. The beat frequency signal undergoes high-frequency component rejection *via* a fifth-order LPF. The sampling module employs a 14-bit, 10 Msps SAR-type ADC. Sampling accuracy stability is controlled by a phase-locked clock driven by an external temperature-compensated crystal oscillator (TCXO), achieving system sampling jitter below ± 1.5 ps RMS.

To achieve the system-level timing coherence, a hardware clock tree-based synchronisation scheme is employed. The master clock is distributed *via* programmable dividers to critical nodes, such as the DDS, ADC, and microcontroller, ensuring microsecond-level synchronous operation for signal modulation, sampling, and control links. The data interface features dual-channel SPI and high-speed USB links, supporting raw beat frequency

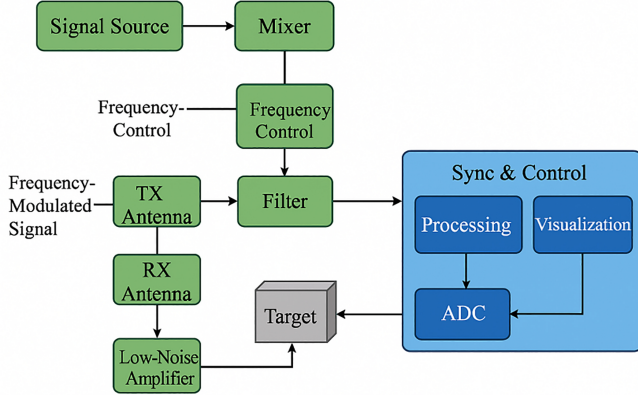


Figure 4. Hardware topology diagram of the automated ranging system.

data upload and control parameter download. All modules are encapsulated using a shielded isolation design and interconnected *via* high-frequency coaxial links, delivering EMI immunity exceeding -65 dBc. This significantly enhances system stability and signal integrity in industrial-grade interference environments.

4.2 Visualisation Software Framework Design

The visualisation software framework of the FMCW ranging system is structured around real-time rendering, system feedback, and parameter monitoring objectives. It adopts a three-layer modular architecture with strict data integrity, thread-level concurrency, and closed-loop task scheduling, as illustrated in Fig. 5.

(1) Bottom Layer – Data Input and Preprocessing:

This layer receives measurement outputs, such as range estimates, spectral vectors, and temperature data *via* USB/serial/Wi-Fi interfaces. Data packets are encapsulated using structured message protocols. A typical message structure is defined as:

```
struct MessageFrame {
    uint8_t signal_type;
    uint32_t timestamp;
    uint8_t channel_id;
    uint8_t error_flag;
    float payload128;
};
```

(2) Middle Layer – Task Control and Scheduling:

An asynchronous, non-blocking message queue system manages data channels and performs anomaly detection, filtering, normalisation, and frame synchronisation. Each channel is scheduled based on time-stamped frames, and the maximum dispatch latency is capped at 30 ms to ensure control loop responsiveness.

(3) Top Layer – Graphical Rendering and Visualisation:

Utilising OpenGL and Qt5, the rendering stack supports waveform plots (range $R(t)$), spectral curves (FFT of f_b), and phase drift graphs ($\varphi(t)$). Up to four channels can be updated in parallel using GPU-side frame buffer objects (FBOs), with a peak frame rate of 12 fps.

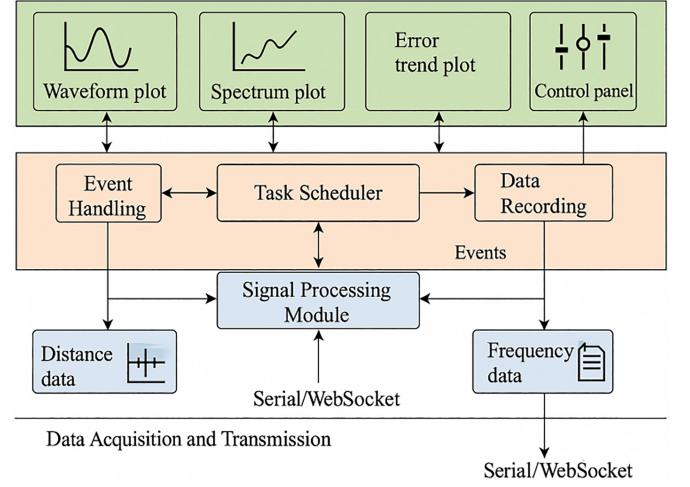


Figure 5. Functional structure and module communication logic diagram of visualisation software.

The refresh interval satisfies

$$T_{\text{refresh}} \leq \frac{1}{f_{\text{frame}}} \leq 150\text{ms} \quad (11)$$

Modules communicate *via* bidirectional message buses, and all messages are parsed into multi-field packets controlled by a master thread. Under test conditions, the system maintains frame sizes ≤ 32 KB, a frame error rate $< 0.6\%$, and supports stable deployment on embedded systems and host terminals with excellent portability and scalability [18].

4.3 Automated Range-Finding Process and Interaction Control Mechanism

The control mechanism of the automated ranging system centers on module state-driven operation, establishing an integrated system control flow encompassing data acquisition, parameter scheduling, anomaly response, and feedback loops [19]. As illustrated in Fig. 6, the system control logic is modelled as a state transition directed graph. The state set comprises four states: Idle, Active, Error, and Reset. System control signals drive state transitions, forming a closed-loop control chain.

During initialisation, the system loads parameter sets transmitted *via* external configuration channels, including frequency modulation bandwidth, sweep period, and sampling rate. Subsequently, the DDS signal source and frequency modulation module are activated. After RF transmission, signals reflect off targets to form echoes. The receive chain processes these through LNA amplification, mixing, and low-pass filtering before inputting to the ADC. Interference signal data enters the data processing module for FFT-based carrier frequency extraction and distance calculation.

Following each data frame processing, the control logic executes decision logic *via* a state machine, setting amplitude thresholds (determined by the dynamic baseline update algorithm), main frequency offset thresholds, and phase drift rate as system operational monitoring

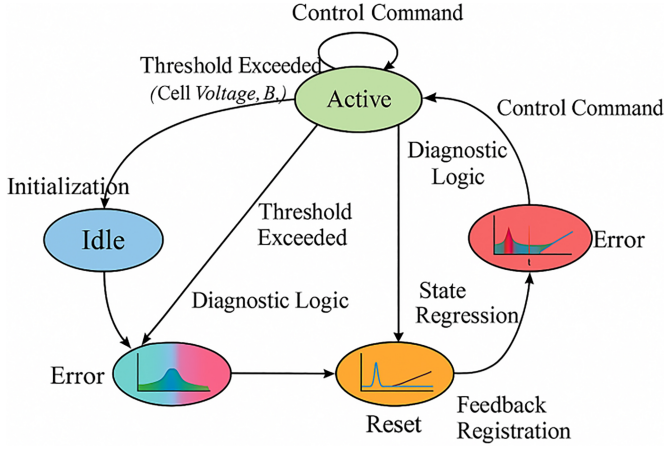


Figure 6. Control state machine transition model diagram.

indicators. If any indicator exceeds its limit, the system enters Error state. The feedback module responds by setting flag bits, masking ranging data uploads, and transmitting fault response commands. The controller interrupt signal triggers link suspension and prepares for state rollback.

To support hot parameter updates during operation, the system employs a dual-buffered parameter register mechanism. Parameter stack switching is performed *via* external control commands while the control state machine is in the Active state. The parameter switching process employs a synchronised control strategy based on the cached register queue, preventing ranging link desynchronisation or interruptions. This enables dynamic system reconfiguration and hot-loading of configurations without service disruption. The entire workflow features event-response coupling, anomaly detection and judgment, and closed-loop self-stabilising regulation, ensuring stable ranging operations under diverse working conditions.

5. Signal Processing and Distance Calculation Algorithm Implementation

5.1 Data Acquisition and Preprocessing

The data acquisition module utilises a 14-bit high-precision successive approximation ADC with a sampling rate of 10 Msps to capture the beat frequency signal output from the LPF after mixing [20]. Within the acquisition chain, a 10 MHz reference frequency is first generated by the clock synchronisation module. This reference is then distributed to the signal source and ADC after frequency division and phase locking, ensuring an integer multiple relationship between the system sampling rate and the frequency modulation period. Before entering the processing channel, the sampled signal passes through an anti-aliasing filter (5th-order Butterworth type, cutoff frequency 1.2 MHz) to suppress high-frequency artifacts. Subsequently, the system employs a windowed FFT to transform the time-domain signal into the frequency domain. The commonly used window type is the Hamming window, which exhibits frequency-domain side lobe suppression exceeding 48 dB.

To enhance the robustness of beat frequency component recognition, the system incorporates wavelet transform denoising and normalisation processing, employing a multiscale threshold function to suppress low-amplitude high-frequency disturbances. The preprocessed signal is then fed into the calculation module for frequency peak extraction and fitting operations. Key parameter settings are shown in Table 2.

5.2 Range Estimation Algorithm

The core of distance calculation in FMCW ranging systems lies in high-precision identification of beat frequency signals and dynamic error compensation. The system first performs an FFT on preprocessed sampled signals to extract their dominant frequency component f_b . A window function is applied to suppress spectral leakage, and a frequency domain fitting algorithm is introduced for refined frequency estimation. Within the main lobe interval, the system constructs a high-order interpolation function using the logarithm of multi-point frequency-amplitude pairs [21]. Combined with a Gaussian model to fit the main peak, this yields the precise center frequency $\hat{f}_b$. To mitigate the limitation of FFT bin resolution on frequency estimation accuracy, a least-squares fitting algorithm is introduced for error optimisation of local spectral features. The fitting function is defined as

$$A(f) = a \times e^{-\left(\frac{f - \hat{f}_b}{\sigma}\right)^2} \quad (12)$$

where $A(f)$ represents the amplitude corresponding to the frequency point f , $\hat{f}_b$ denotes the center of the beat frequency to be estimated, σ indicates the spectral width, and a is the amplitude constant. Substituting $\hat{f}_b$ into the distance analytical expression $R = \frac{c \times \hat{f}_b}{2S}$ enables quantitative calculation of the target distance. To address phase drift errors caused by non-ideal mixing and sampling delays in the system, a phase recovery mechanism based on the Hilbert transform is introduced. The instantaneous phase $\phi(t)$ is extracted from the complex envelope of the signal, and a dynamic compensation factor is constructed:

$$\Delta f_\phi = \frac{1}{2\pi} \times \frac{d\phi(t)}{dt} \quad (13)$$

This formula corrects dynamic phase drift in beat frequency estimation, demonstrating robust performance under severe target acceleration variations or significant temperature disturbances. Table 3 shows the sensitivity of ranging accuracy to parameters in frequency identification and distance calculation, revealing significant correlations between beat frequency extraction precision and system bandwidth, window function selection, and SNR.

5.3 Visualisation Result Analysis Module

The visualisation result analysis module comprises three synergistic components: a real-time rendering engine, a frequency-domain feature extraction pipeline, and a structured data management system. This configuration ensures multidimensional representation and traceable

Table 2
Parameter Configuration

Parameter Module	Parameter Name	Value/Type	Description
ADC sampling module	Resolution	14 bits	Provides high-precision amplitude resolution capability.
	Sampling rate	10 Msps	Meets the requirement for a maximum 10 m ranging resolution.
Anti-aliasing filter	Filter type	5th-order Butterworth	Flat passband response ensures full preservation of main signal amplitude.
	Cutoff frequency	1.2 MHz	Exceeds theoretical maximum beat frequency (1 MHz) configuration.
Preprocessing window function	Type	Hamming window	High spectral side-lobe suppression capability, preventing peak drift.
Noise reduction module	Method	Multi-scale wavelet threshold compression method	Adaptive multiband filtering to enhance SNR.

Table 3
Analysis of Key Distance Estimation Parameters' Impact on Accuracy

Parameter Name	Parameter Range	Influence Mechanism	Ranging Error Impact (Root Mean Square)
FFT sampling points	1024/2048/4096	Improved frequency domain resolution	Decrease of approximately 0.5–1.2 mm
Window function type	Hamming/kaiser/blackman	Side lobe suppression capability versus main lobe broadening trade-off	Kaiser window minimises error
Signal-to-noise ratio (SNR)	25 dB/35 dB/45 dB	Noise interference beat frequency detection	SNR < 30 dB error significantly increases
Phase drift frequency offset term	0.5–5kHz dynamic variation	Causes beat frequency offset	Requires introduction of compensation model
Distance solution bandwidth B	250–1,000 MHz	Affects theoretical resolution R	Larger B results in smaller error

storage of frame rate, distance, and error information at high temporal resolution. First, a short-time Fourier transform (STFT) is applied to the sampled time-domain signal to obtain a high-resolution time-frequency spectrum [22], defined as

$$\text{STFT} \{x[n]\}(m, \omega) = \sum_{n=-\infty}^{\infty} x[n] w[n - mR] e^{-j\omega n} \quad (14)$$

where $x[n]$ is the discrete-time signal, $w[\cdot]$ is the window function, m is the frame index, R is the frame shift sample count, and ω is the angular frequency. Through ridge detection and quadratic interpolation enhancement, the instantaneous beat frequency trajectory $f_b(t)$ is extracted and transformed into the distance domain *via* the mapping function $d(t) = \frac{c}{2S} f_b(t)$ for rendering stack invocation.

To estimate spectral energy, the Welch method averages the power spectra of each segment, expressed as

$$\hat{P}_{xx}(f) = \frac{1}{K} \sum_{k=1}^K \frac{1}{U} |X_k(f)|^2 \quad (15)$$

where X_k is the window-weighted FFT for segment k , K is the segment number, and U is the window function

power normalisation constant. Distance-time and error curve plots are generated through a multi-point fitting and residual analysis workflow, with fitting coefficients solved using the normal equation:

$$\hat{\mathbf{a}} = \left(\mathbf{V}^T \mathbf{V} \right)^{-1} \mathbf{V}^T \mathbf{y} \quad (16)$$

where $\mathbf{V}$ represents the Vandermonde matrix, $\mathbf{y}$ denotes the observed distance vector, $\hat{\mathbf{a}}$ signifies the fitted polynomial coefficients, and the residual sequence $\Delta R = R_{\text{est}}(t) - R_{\text{fit}}(t)$ is utilised for error analysis visualisation and threshold alerting modules. All analysis results are uniformly written into a structured time-series database, partitioned and indexed by device ID and task batch. Core fields include: timestamp, beat frequency, estimated distance, SNR, instantaneous phase, and environmental parameters, such as temperature and humidity. The database employs columnar compression and multi-threaded asynchronous write mechanisms to enhance query performance and ensure data consistency, supporting high-concurrency data ingestion at > 10k entries per second.

6. Experimental Validation and Performance Evaluation

6.1 Experimental Setup and Parameter Configuration for Automated Ranging System

To comprehensively evaluate the ranging performance, dynamic adaptability, and real-time processing stability of the proposed FMCW-based automated ranging system, a structured experimental platform was constructed that aligns with the full signal-processing workflow. The experiment is organised around four key modules: transmission configuration, reception and digitisation, signal processing and visualisation, and data logging and evaluation.

In the transmission segment, an LFM signal is emitted with +10 dBm power and 500 MHz sweep bandwidth, centered at 77 GHz. The sweep cycle is fixed at 1 ms to ensure appropriate time-frequency resolution during target motion [23]. These parameters are chosen based on the relationship between bandwidth and range resolution ($\Delta R \approx 0.15 \text{ c/B}$), yielding a theoretical spatial resolution of approximately 0.3 m. The choice of 500-MHz bandwidth matches the optimal trade-off between resolution and system bandwidth constraints, as discussed by Heo *et al.* [16]. On the acquisition side, the receiver utilises a 14-bit SAR-ADC with a 10-Msps sampling rate. Synchronisation across subsystems is maintained by a 10-MHz high-stability reference clock. This design reflects practical considerations for real-time signal digitisation in manufacturing environments. Signal processing is conducted using an STFT framework with a 4096-point FFT and Hamming windowing, ensuring a frequency bin resolution of approximately 2.44 kHz. Phase drift and group delay are compensated *via* a hybrid Hilbert transform and dynamic phase estimation algorithm, structurally modelled following the implementation rationale outlined.

For data management, a time-series database architecture is employed, with field entries, including beat frequency, distance, SNR, temperature, and estimated phase offset. This enables efficient storage, batch compression, and historical trend analysis. A complete summary of parameter settings is provided in Table 4.

6.2 System Modelling Accuracy and Ranging Stability Analysis

To validate the applicability and stability of the proposed FMCW system model across varying distance ranges, comparative experiments were conducted involving theoretical distances, simulated model outputs, and actual measured values. The analysis spanned three distance intervals: short (1–5 m), medium (5–20 m), and long range (20–50 m). All tests adopted a uniform 200-MHz sweep bandwidth, 10-Msps sampling rate, and a fixed 12-dBi antenna gain. After FFT processing of the downconverted beat signals, target distances were estimated using standard range formulas.

As shown in Table 5, within the short-range interval, the average deviation between the simulation model and

theoretical values remained within $\pm 0.8 \text{ cm}$. In long-range scenarios, the error increased marginally due to frequency offset accumulation, yet remained below 3 cm in all cases, demonstrating high structural consistency across scenarios [24]. These observations are consistent with the link error model proposed, where spectral drift caused by non-ideal frequency modulation leads to range bias [25].

To further assess measurement consistency, 100 consecutive ranging trials were conducted at each interval. The standard deviation σ was computed as

$$\sigma = \frac{1}{N} \sum_{i=1}^N (d_i - \bar{d})^2 \quad (17)$$

where d_i denotes individual ranging output, $\bar{d}$ is the mean distance, and N is the total number of samples. Results indicate that standard deviation remained under 1.5 cm across all ranges, with mid-range (5–20 m) showing optimal stability. This improvement is largely attributed to the frequency linearity enhancement and phase noise suppression mechanism derived from adaptive clock jitter modelling, as validated by Zhao *et al.* [26]. The resulting beat frequency spectrum exhibited narrow peak distributions, thereby improving distance resolution reliability under varying test conditions.

6.3 Automated Control and Performance Optimisation Validation Experiments

To evaluate the effectiveness of closed-loop control strategies in improving the stability and accuracy of FMCW-based automated ranging systems, a control framework incorporating real-time disturbance estimation, adaptive bandwidth regulation, and error feedback compensation was developed. The core module adopts a proportional-integral (PI) control structure, designed to dynamically adjust the frequency modulation slope and ADC sampling rate based on the iterative deviation in ranging results [27]. The control law is defined as

$$\Delta u(k) = K_p e(k) + K_i \sum_{i=1}^k e(i) \quad (18)$$

where $e(k)$ denotes the ranging error at iteration k , and K_p, K_i represent the proportional and integral coefficients, respectively. This enables real-time modification of frequency sweep parameters and clock timing, effectively suppressing the influence of target reflectivity variation, phase noise, and link instability. The control strategy was implemented following the adaptive PI-based self-regulation scheme discussed, which emphasised system-level convergence in dynamic feedback environments [28].

Two experimental conditions were constructed: (1) a stable scenario with minimal interference, and (2) a compound interference scenario incorporating artificial occlusion, multipath wall reflections, and thermal drift induced by controlled ambient variation. The test targets were placed at 0.5–5 m, with each distance repeated over 20 trials. Performance was assessed using four metrics: maximum deviation, average deviation, stabilisation time

Table 4
Experimental Parameters and Configuration of Automated Ranging System

Module Category	Parameter Name	Configuration Value/Type	Description
Transmitter module	Transmit power	+10 dBm	Meets high signal-to-noise ratio requirements for indoor direct-field applications.
	Sweep bandwidth	500 MHz	Corresponding theoretical distance resolution: 0.3 m.
	Scan cycle	1 ms	Guarantees frequency-change capture capability in dynamic scenarios.
Receive and sampling chain	ADC resolution	14-bit	Ensures amplitude resolution and spectral stability.
	Sampling rate	10 Msps	Meets sampling theorem requirements for maximum beat frequency (approximately 1 MHz).
	Clock frequency	10 MHz	Provides synchronisation reference.
Processing and visualisation module	STFT window type	Hamming	Suppresses spectral leakage and improves beat-frequency peak recognition accuracy.
	FFT length	4096	Enhances frequency-domain resolution (approximately 2.44 kHz).
	Phase compensation mechanism	Hilbert + Dynamic Drift Estimation	System delay and phase disturbance correction.
Data recording and management module	Database type	Time-series database (partitioned storage)	Supports batch compression and efficient queries.
	Storage fields	Distance, beat frequency, phase, SNR, temperature, etc.	For subsequent performance evaluation and historical comparison analysis.

Table 5
Comparison of Ranging Model Accuracy Results

Range interval	Theoretical distance/m	Simulated distance/m	Actual distance/m	Average error/cm	Maximum error/cm
1–5	3.00	2.992	2.995	0.5	0.8
5–20	12.00	11.987	11.991	0.7	1.2
20–50	35.00	34.974	34.969	1.5	2.9

(duration for error to remain within ± 1 mm for ≥ 100 ms), and response time (time from disturbance onset to first stabilisation).

As summarised in Table 6, under compound interference, the maximum deviation was reduced from 14.2 to 3.7 mm post-control deployment—a 74% improvement. Average deviation decreased from 6.5 to 1.8 mm, while stabilisation time and response time improved by 62.9% and 30.2%, respectively. These results demonstrate the enhanced error convergence and disturbance suppression capabilities of the automated control module, aligning with recent findings on feedback-optimised embedded systems [29].

6.4 System Robustness

System robustness performance was validated through perturbation injection experiments, covering four typical disturbance sources: channel blocking, amplitude attenuation, environmental noise superposition, and phase perturbation [30]. The perturbation models were defined as follows: ① Blocking modelled as a short-term signal interruption function; ② Amplitude attenuation modelled as an exponential-decaying envelope; ③ Noise superimposed using band-limited Gaussian white noise, reducing the SNR to 10–25 dB; ④ Phase disturbance superimposed onto the carrier phase *via* a random walk. Experiments employed

Table 6
Comparison of Ranging Performance Metrics Before and After Automated Control Optimisation

Experimental conditions	Control strategy	Maximum deviation (mm)	Average deviation (mm)	Stabilisation time (s)	Response time (ms)
No disturbance	No control	3.2	1.1	0.72	116
	Automatic control	1.5	0.6	0.38	94
Multiple interference	No control	14.2	6.5	1.24	182
	Automatic control	3.7	1.8	0.46	127

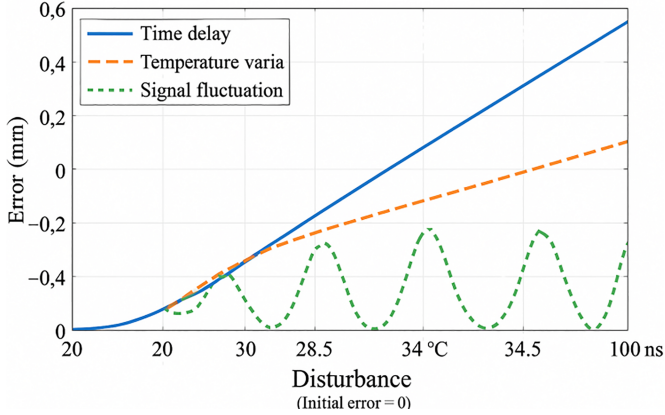


Figure 7. Error trajectory under interference conditions.

univariate excitation to inject disturbances sequentially, recording distance estimation results before, during, and after disturbance recovery. Each test set was repeated 30 times, with results averaged. Robustness evaluation metrics included maximum transient deviation $\Delta_{\max}$, recovery time T_r , and steady-state offset Δ_{drift} .

Figure 7 illustrates the temporal trends of error trajectories. Following short-term occlusion and phase disturbance injection, error transient fluctuations increased, with $\Delta_{\max}$ peaks reaching approximately ± 7.8 mm. Under the feedback compensation mechanism, the error curve converged in an exponentially decaying manner, with the recovery time T_r maintained within 0.8 s and the steady-state drift Δ_{drift} not exceeding ± 0.6 mm [31]. Under the scenario of superimposed multi-source disturbances, the system did not experience ranging link desynchronisation or drift accumulation, and the output continuity remained stable, indicating that the implemented signal chain compensation mechanism effectively suppresses random disturbances.

7. Conclusion

This study presents a closed-loop FMCW-based automated ranging system integrating signal modelling, beat spectrum analysis, phase error correction, and dynamic feedback control. The proposed architecture forms a unified simulation-testing-control pipeline, ensuring consistency in parameter application and result reproducibility. A discrete PI-based controller governs adaptive modulation and sampling rate adjustments, while a phase-compensated

spectral feature extractor enhances robustness under complex noise and reflection conditions. Experimental results confirm the system's capability to maintain an RMSE of ± 0.51 mm, with a maximum deviation of 3.7 mm and a convergence time below 0.46 s under compound disturbances, aligning with engineering requirements of real-time tracking and stability assurance.

The platform demonstrates strong engineering scalability and modular deployment controllability, adapting to high-frequency acquisition, interference perception, and autonomous parameter correction. Structurally, the system conforms to real-time embedded processing pipelines and supports decoupled storage for batch feature vectors, similar to the embedded design schemes explored by Wang *et al.* enhancing data traceability and operational flexibility.

Future work will focus on three key directions: (1) introducing an MIMO-based echo model tailored to layered heterogeneous targets for improved spatial resolution; (2) optimising low-power SoC-level deployment, reducing real-time processing latency and energy consumption; and (3) constructing nonlinear response modelling mechanisms for adaptive prediction under dynamic link drift and non-Gaussian disturbances. These directions aim to further enhance the fidelity and robustness of FMCW-based intelligent perception systems in real-world deployment scenarios.

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