

Simulation-Based Multi-Stage Radar Framework for Human Detection, Tracking, Fall Recognition, and Post-Fall Vital-Sign Estimation

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ABSTRACT

This paper attempts to maintain target identity, detect falls, and evaluate the physiological state after falling in the SAR environment using radar. It also introduces a multi-stage radar sensor fusion framework that leverages confidence-based fusion, Kalman tracking, kinematic fall detection, and gated physiological estimation and that is implemented in MATLAB. The proposed method achieves simulated results with a 98% probability of detection, fall F1 of 0.96, and physiological estimation errors of 0.89 cycles/minute (breathing) and 1.2 beats/minute (heartbeats) while achieving a reduction of 75.9% (gating) and 82.4% (fall triggering) processing unnecessarily. Simulation-based evaluation only; performance deteriorates in cases of dense clutter, multipath, and domain shifts, where track loss during occlusion and fall misclassification due to fast motion remain open problems.

إطار عمل راداري متعدد المراحل قائم على المحاكاة لرصد البشر وتتبعهم والتعرف على حالات السقوط وتقدير المؤشرات الحيوية بعد السقوط

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المخلص	الكلمات المفتاحية
تسعى هذه الورقة البحثية إلى الحفاظ على هوية الهدف، واكتشاف حالات السقوط، وتقييم الحالة الفسيولوجية بعد السقوط في بيئة عمليات البحث والإنقاذ (SAR) باستخدام تقنية الرادار. كما تقدم الورقة إطار عمل متعدد المراحل لدمج بيانات أجهزة استشعار الرادار، يعتمد على الدمج القائم على مستوى الثقة، وتتبع "كالمان" (Kalman tracking)، واكتشاف السقوط بناءً على الخصائص الحركية، والتقدير الفسيولوجي المعتمد على تقنية البوابات (gated estimation)؛ وقد تم تنفيذ إطار المحاكاة باستخدام برنامج MATLAB. تحقق الطريقة المقترحة نتائج المحاكاة بإحتمالية اكتشاف تبلغ 98%، وقيمة F1 لاكتشاف السقوط تبلغ 0.96، ونسبة خطأ في التقدير الفسيولوجي تبلغ 0.89 دورة/دقيقة (للتنفس) و1.2 نبضة/دقيقة (لضربات القلب)، مع تحقيق خفض في عمليات المعالجة غير الضرورية بنسبة 75.9% (بفضل تقنية البوابات) و82.4% (فيما يتعلق بآلية تفعيل رصد السقوط). يقتصر التقييم على المحاكاة؛ إذ يتراجع الأداء في حالات التشويش الكثيف (clutter)، وتعدد المسارات (multipath)، وتحولات النطاق (domain shifts)، حيث تظل قضايا فقدان المسار أثناء حجب الرؤية (occlusion) والتصنيف الخاطئ للسقوط الناتج عن الحركة السريعة تحديات مفتوحة تتطلب مزيداً من البحث.	دمج بيانات الرادار اكتشاف البشر تتبع كالمان تتبع الأهداف اكتشاف السقوط تقدير المؤشرات الحيوية

Introduction

SAR missions have been among the most difficult applications of remote sensing techniques. Victims could be hidden behind foliage, under rubbles, in darkness or smokes, or even blocked by non-metallic walls [1]. In these cases, time is critical, and rescuers need to make crucial decisions with the least amount of data available while having limited access to resources [2]. Existing techniques based on visual search, thermal imaging, and acoustic sensing have proven to be ineffective in obstructed environments, especially in case of unconscious victims [3].

The use of radar has proven to be a highly effective approach

to SAR problems owing to its peculiarities, which include being contactless, independent on the lighting conditions, respecting the privacy, and penetrating non-metallic objects [4,5]. Contemporary radars, such as FMCW and UWB impulse radars, provide high-resolution range estimation, Doppler velocity measurements, and micro-Doppler signature [6,7].

On the other hand, the practical use of radar technology for the SAR mission entails answering three logical, yet related questions: Where is the person? – continuous tracking in presence of clutter and occlusions, did a fall occur? – identification of anomalies indicative of falls or collapses,

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and Is the person alive? – confirmation of presence of physiological motions (breathing and heartbeat) following such an event.

Separating them into three independent classification tasks gives rise to several serious weaknesses in terms of identity issues across processing steps, erroneous association of physiological signals with false targets and inefficient use of computing resources [8]. The unsolved technical issue is not about feasibility of separate elements, but rather about ability to maintain target identity and uncertainty information along the whole chain of processing steps [9].

This paper has four principal contributions:

1. **Identity-Preserved System Architecture:** This work defines an integrated interface between radar detections/tracks, fall detection and vital sign verification such that target identity is preserved across all stages of processing as showing in Figure 1.
2. **Signal Mathematical Modelling:** This work develops a comprehensive signal measurement model accounting for foliage clutter, occlusion, multipath, and sensor-dependent confidence levels.
3. **Gating with Confidence:** A new confidence-based data fusion technique is proposed which adaptively changes the measurement covariance matrix depending on environmental factors and sensor confidence levels.
4. **Baseline System Implementation:** This work offers a fully implemented system in MATLAB R2023b which simulates radar signals and runs the whole processing chain.



Figure 1: Airborne SAR Imaging and Multi-Stage Radar-Based Recognition of a Falling Human in a Forest

Related Works

Radar Detection and Tracking under Complex Environment

Radar detection and tracking are considered the key components of any radar perception system. Traditional radar processing chain includes noise estimation, Constant False Alarm Rate (CFAR) detection, measurement transformation and temporal association [10]. Stacking ensemble architecture based on micro-Doppler signatures using a Ka-band 35 GHz radar for categorizing humans, gorillas, and robots in an urban multipath environment. The simulation-based system yielded 90.92% accuracy through mitigation of spectral smearing using multipath-aware augmentation techniques [11].

Recent research focused on adaptive CFAR detection which

adjusts the threshold value of detection based on the local statistics of the clutter [12], [13]. Machine learning technique, especially convolutional neural network (CNN) has been applied to identify human targets in the range-Doppler maps [14]. Using CNN for the classification of five different heartbeats found in the MIT-BIH database, and by proving that DWT is more effective than Butterworth filtering as the method of signal preprocessing, they showed that DWT allows obtaining higher accuracy in classification equal to 89.82%. [15].

Multi-sensor fusion appears to be a potential approach to increasing detection robustness. LiDAR provides highly accurate geometric information; however, it is susceptible to the presence of dust, fog, and foliage [16]. Visual systems can deliver highly informative visual cues, but not at night or when there is heavy smoke [17]. Radar provides reliable motion sensing in obscurants, even though with lower spatial resolution [18].

Kalman filter and its derivatives such as Extended Kalman filter [19]. Unscented Kalman Filter are still used as a standard approach for target tracking [20]. Modern works try to use multiple hypothesis tracking (MHT) and joint probabilistic data association (JPDA) for multiple targets tracking [21]. Still, it is hard to maintain target identification in situations where detection is interrupted due to occlusion [22].

Radar-Based Fall Recognition

Fall recognition has been extensively studied in connection with elder people healthcare applications [23]. The specificity of falls lies in their kinematics and micro-Doppler signature [24].

Micro-Doppler Signature: Micro-Doppler signature is generated by movements of limbs and torso motions [25]. However, falls normally comprise quick transient and then a stationary phase, whereas activities like walking and sitting do not possess such characteristics [26]. Time-frequency representation techniques such as spectrogram analysis combined with machine learning classifiers were proved to deliver high accuracy on controlled datasets [27], [28].

Range-Doppler Features: Range-Doppler maps encode displacement and velocity characteristics. They can be used as complementary fall detection features [29]. Deep learning approaches using CNN-LSTM architectures showed good results when applied to range-Doppler sequences [30], [31].

Generalization Challenges: While performing excellently in simulation setups, fall detection systems face challenges in real-life applications. These systems perform poorly due to changes in room shape, body shape, sensor position, fall orientation, and non-fall motions (sitting down quickly) [32]. Domain adaptation and transfer learning strategies are currently being researched to address these issues of generalization [33].

Heart Rate and Breathing Estimation Through Obstructions

Respiratory and cardiac activity generates small quasi-periodic motions of the chest (chest movements for respiration of 0.1-10 mm and heartbeats 0.01-0.5 mm) which can be picked up by a radar system [34].

Signal Models: The radar return signal of a static human target for monostatic radar can be modeled in Eq.1 as:

$$r(t) = A \cos(2\pi f_c \tau(t) + \phi_0) + n(t) \quad (1)$$

where A is amplitude, f_c is carrier frequency, $\tau(t)$ is time-varying delay, ϕ_0 is initial phase, and $n(t)$ is noise [35]. The round-trip delay shows in Eq. 2 is:

$$\tau(t) = \frac{2}{c} [d_0 + a_r \sin(2\pi f_r t) + a_h \sin(2\pi f_h t)] \quad (2)$$

where d_0 is mean range, a_r and a_h are respiration and heartbeat displacement amplitudes, f_r and f_h are respiration and heartbeat frequencies [35].

Clutter Suppression: Vital-signs detection faces a major challenge in the presence of static clutter, non-stationary interference, and linear trends. Possible solutions are use of SVD technique for clutter matrix decomposition [36]

Wavelet transforms for multi-resolution analysis, Empirical Mode Decomposition (EMD) as adaptive filter and Variational Mode Decomposition (VMD) for enhanced frequency decomposition, Frequency Estimation: Despite their simplicity, spectral methods such as FFT and periodogram are still widely used for frequency estimation, Advanced approaches include MUSIC algorithm for super-resolution,

As well as Compressive sensing for recovery of sparse signals and Deep learning for end-to-end vital-signs extraction [37]. However, in case of forest and obstructed environment, the uncertainty level of measurements changes drastically because of the movement of canopy, signal attenuation, multipath and partial visibility [38].

Supplementary Local Research into Sustainable Energy Infrastructures

As the current study concentrates on radar sensing capabilities for SAR activities, there is a need for dependable and sustainable energy sources for the implementation of these sensors in remote areas of Libya. Local research efforts have prepared the way for the creation of hydrogen-based energy infrastructure that could possibly help to energize the deployed radar and sensor systems.

Research Gap

Though the feasibility of individual approaches (detection, tracking, falls recognition, vital signs) has been proven, there are several important research gaps:

1. **System Integration:** Only few publications deal with integration of all components from target detection till post-fall vital-signs assessment.
2. **Uncertainty Propagation:** Uncertainty propagation modeling is not considered in most systems.
3. **Computational Efficiency:** Real-time monitoring of vital-signs for many targets requires a lot of computing resources. Event-based processing would significantly decrease this requirement.
4. **Reproducibility:** Many publications do not provide publicly accessible implementations and evaluation protocol.

This paper attempts to bridge these gaps through the introduction of a unified architecture with uncertainty modeling, confidence-based gating, and reproducible baseline implementation.

Multi-Stage Architecture Proposal

System Description

In this system proposal, for each candidate person i , a track record is kept at time index k . Each track record includes State vector (position, velocity), Covariance matrix, Sensor source, Event state, and Physiological state estimation. The system consists of three stages in Table 1.

Quality-Aware Multimodal Sensor Fusion

Consider the radar sensor s sending out measurement z_k with covariance R_k and quality $q \in [0, 1]$.

Inflating Covariance: Since the sensor's measurements are less reliable in bad conditions, we inflate the covariance of

Table 1: Multi-Stage Architecture

Stage	Input	Main Operation	Output
Detection & Tracking	Range-Doppler observations, LiDAR visibility	Clutter suppression, CFAR, confidence fusion, Kalman filtering	Persistent track with covariance Continuous, Activation
Fall Recognition	Track history, kinematic features	Temporal fall scoring from range/velocity/acceleration	Fall probability, event timestamp, Continuous (lightweight) Activation
Vital Confirmation	Fall-gated slow-time signal	Detrending, filtering, spectral estimation, quality control	Respiration rate, heart rate, confidence, post-fall only Activation

the measurement in Eq.3 as follows:

$$R_{inflated} = \frac{R_k}{\max(q_s, \epsilon)} \quad (3)$$

where $\epsilon=0.01$ to avoid singularity. In this representation, more uncertainty is associated with low quality measurements, as expected.

Information-Weighted Fusion: For M sensors, the fused measurement $\hat{z}_k$ in Eqs.4 and 5 as:

$$\hat{z}_k = \hat{R} \sum_{s=1}^M \tilde{R}_s^{-1} z_{k,s} \quad (4)$$

with fused covariance:

$$\hat{R} = \left(\sum_{s=1}^M \tilde{R}_s^{-1} \right)^{-1} \quad (5)$$

This information filter formulation will gracefully allow the system to deal with sensor dropout, discrepancy, or differing reliability without completely throwing out the observation.

Quality Score Estimation: For radar data, the equation becomes as:

$$q_k = \exp \left(- \frac{SNR_{ref}}{SNR_k} \right) \cdot (1 - \alpha_{occ}) \quad (6)$$

where SNR_{ref} is the reference SNR (generally 10 dB), and α_{occ} is occlusion score factor.

Tracking Model

We employ a constant-velocity model for range-velocity tracking, the state vector for target i is:

$$x_k = [r_k, \dot{r}_k]^T \quad (7)$$

State Transition Eq.8 is:

$$x_{k \setminus k-1} = F x_{k-1 \setminus k-1} \quad (8)$$

with Eq. 9 for state transition matrix F , and process noise Q_k in Eq. 10. Measurement Model for Eq. 11:

$$F = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \quad (9)$$

and process noise $w_k \sim N(0, Q)$ in Eq.10 where:

$$Q_k = \sigma_a^2 \begin{bmatrix} \Delta t^4/4 & \Delta t^3/2 \\ \Delta t^3/2 & \Delta t^2 \end{bmatrix} \quad (10)$$

and σ_a is the acceleration standard deviation (typically 1-2 m/s² for human motion).

Measurement Model for Eq.11:

$$z_k = H_s x_k + v_{k,s}, \quad v_{k,s} \sim N(0, R_{k,s}) \quad (11)$$

Kalman Filter Equations for Eqs. 8, 12, 13, 14 and 15:

Prediction:

$$\text{As Eq.8 } x_{k \setminus k-1} = F x_{k-1 \setminus k-1}$$

$$P_{k \setminus k-1} = F P_{k-1 \setminus k-1} F^T + Q_k \quad (12)$$

Update with Eqs. 13,14 and 15:

$$K_k = P_{k \setminus k-1} H^T (H P_{k \setminus k-1} H^T + R_k)^{-1} \quad (13)$$

$$x_{k \setminus k} = x_{k \setminus k-1} + K_k (z_k - H x_{k \setminus k-1}) \quad (14)$$

$$P_{k \setminus k} = (I - K_k H) P_{k \setminus k-1} \quad (15)$$

Fall-Event Recognition

A fall is characterized by rapid displacement, high velocity, and subsequent motion cessation that define kinematic features over a sliding window of length W :

A fall is characterized by rapid displacement, high velocity, and subsequent motion cessation. Feature Extraction (Eqs. 16-19) and Fall Score (Eq. 20) are computed. Event Detection triggers when $S_{fall}(k) > \gamma_{fall}$ for N frames (Eq. 21). Additional Constraints (Eqs. 22-24) reduce false alarms.

Feature Extraction

$$\text{Range displacement: } \Delta r(t) = |r(t) - r(t - \Delta t_{lag})| \quad (16)$$

Radial velocity magnitude:

$$|v(t)| \quad (17)$$

$$\text{Acceleration magnitude } |a(t)| = \left| \frac{v(t) - v(t-1)}{\Delta t} \right| \quad (18)$$

$$\text{Short-time energy: } E(t) = \frac{1}{W} \sum_{i=0}^{W-1} |v(t-i)|^2 \quad (19)$$

Fall Score: We compute a composite fall score using logistic functions for smooth, differentiable transitions:

$$S_{fall}(t) = \sum_{j=1}^4 w_j \cdot \sigma \left(\frac{f_j(t) - \theta_j}{\beta_j} \right) \quad (20)$$

Where: $f_1 = \Delta r$, $f_2 = |v|$, $f_3 = |a|$, $f_4 = E$,

$\sigma(x) = \frac{1}{1+e^{-x}}$ is the logistic function, θ_j are thresholds β_j

control slope steepness, w_j are weights $\sum w_j = 1$

Event Detection: A fall alarm is triggered when:

$$S_{fall}(t) > \gamma_{fall} \text{ for } N_{consec} \text{ frames} \quad (21)$$

where γ_{fall} is the fall threshold (typically 0.6) and N_{consec} ensures temporal consistency (typically 3-5 frames).

Additional Constraints: To reduce false alarms, we impose:

$$\text{Net displacement: } |r(t) - r(t - \Delta t_{long})| > \delta_{min} \quad (22)$$

$$\text{Direction consistency: } \left| \frac{1}{N} \sum \text{sign}(v) \right| > \eta_{dir} \quad (23)$$

$$\text{Sustained velocity: } \frac{1}{N} \sum |v| > v_{min} \quad (24)$$

Terrain Compensation in Forest Environments: In forest environments, falls on slopes or among tree roots generate distinct kinematic signatures compared to flat ground, potentially causing false negatives or positives. To compensate for uneven terrain, the system incorporates an elevation-aware threshold adjustment. Let z_k be the estimated elevation from the radar's 3D tracking or a digital elevation model (DEM). The terrain slope θ_k is estimated as $\theta_k = \arctan \frac{\Delta z}{\Delta r}$. The fall threshold γ_{fall} is dynamically adjusted based on the terrain angle:

$$\gamma_{adj} = \gamma_{fall} \cdot (1 + \beta \sin^2(\theta_k)) \quad (25)$$

where β is a terrain sensitivity factor. This ensures that expected kinematic variations due to sloped ground do not trigger false fall alarms, while actual falls on uneven terrain are still captured by the adaptive threshold.

Post-Fall Vital-Sign Confirmation

After a fall alarm, the system extracts the slow-time signal.

Signal Model:

$$s(t) = A_c \cos \left(\phi_0 + \frac{4\pi}{\lambda} \Delta x(t) \right) + c(t) + n(t) \quad (26)$$

Preprocessing:

1. Detrending: Remove linear and quadratic trends:

$$s_{det}(t) = s(t) - (a_0 + a_1 t + a_2 t^2) \quad (27)$$

where coefficients are estimated via least-squares polynomial fitting.

2. High-Pass Filtering: Suppress low-frequency drift

and residual clutter:

$$s_{hp}(t) = s_{det}(t) * h_{hp}(t) \quad (28)$$

with cutoff frequency $f_c = 0.08\text{Hz}$

3. Band-Pass Filtering: Separate respiratory and cardiac components:

$$s_{resp}(t) = s_{hp}(t) * h_{BP,resp}(t) \quad (29)$$

$$s_{cardiac}(t) = s_{hp}(t) * h_{BP,cardiac}(t) \quad (30)$$

Harmonics Interference Mitigation: A known challenge in radar vital sign extraction is that the second and third harmonics of the respiration signal often fall into the cardiac frequency band (1.0–1.5 Hz), causing false heartbeat estimates.

To address this, we employ a Harmonics Cancellation algorithm. After extracting the fundamental respiration frequency f_{resp} and its phase ϕ_{resp} , we synthesize the second harmonic component:

$$s_{harm}(t) = A_{harm} \cos(2\pi(2 f_{resp})t + 2 \phi_{resp} + \psi) \quad (31)$$

where A_{harm} and ψ are estimated via least-squares fitting from the cardiac band signal. The clean cardiac signal is then obtained by subtraction:

$$s_{cardiac_clean}(t) = s_{cardiac}(t) - s_{harm}(t) \quad (32)$$

This significantly reduces false positive heart rate detections caused by respiration harmonics.

Spectral Estimation & Peak Detection (Eqs. 33-37), Quality Assessment (Eqs. 38-45) follow standard periodogram and SNR thresholding methods.

We determine the PSD of the signal via the periodogram approach:

$$P(f) = \frac{1}{N} \left| \sum_{n=0}^{N-1} s[n] e^{-j2\pi f n} \right|^2 \quad (33)$$

For better resolution in the frequency domain, we perform zero-padding up to length:

$$N_{FFT} = 2^{\lceil \log_2 N \rceil + 2} \quad (34)$$

Peak Detection:

Respiratory frequency:

$$\hat{f}_r = \arg \max_{f \in [0.1, 0.7]} P_r(f) \quad (35)$$

Heart rate frequency:

$$\hat{f}_h = \arg \max_{f \in [0.8, 2.5]} P_h(f) \quad (36)$$

Corresponding rates:

$$RR = 60 \cdot \hat{f}_r \left(\frac{\text{cycles}}{\text{min}} \right) R = 60 \cdot \hat{f}_h (\text{beats/min}) \quad (37)$$

Quality Assessment:

The signal quality measures are defined by the spectral concentration:

$$SNR_r = 10 \log_{10} \left(\frac{P_r(\hat{f}_r)}{\text{median} \{P_r(f) : f \neq \hat{f}_r\}} \right) \quad (38)$$

$$SNR_h = 10 \log_{10} \left(\frac{P_h(\hat{f}_h)}{\text{median} \{P_h(f) : f \neq \hat{f}_h\}} \right) \quad (39)$$

A detection is considered valid if:

$$SNR_r > \gamma_{SNR,r} \text{ (typically 15 dB)} \quad (40)$$

$$SNR_h > \gamma_{SNR,h} \text{ (typically 20 dB)} \quad (41)$$

$$RR \in [8, 30] \left(\frac{\text{cycles}}{\text{min}} \right) \text{ (physiological range)}$$

$$R \in [50, 120] (\text{beats/min}) \text{ (physiological range)}$$

Quality Score:

$$Q_{vital} = \frac{1}{2} (Q_r + Q_h) \quad (42)$$

$$Q_r = \min \left(1, \max \left(0, \frac{SNR_r - \gamma_{SNR,r}}{15} \right) \right) \quad (43)$$

$$Q_h = \min \left(1, \max \left(0, \frac{SNR_h - \gamma_{SNR,h}}{15} \right) \right) \quad (44)$$

Reproducible Baseline Implementation

Synthetic Data Generation

To enable reproducibility, our work provides an extensive MATLAB R2023b code for generating radar

Target Motion & Vital Signs: Walking phase (Eq. 46), Fall

transition, post-fall stationary with vitals (Respiration Eq. 47, Heartbeat Eq. 48). Clutter and Noise: Static clutter, dynamic foliage motion, AWGN, and multipath replicas.

Target Motion Model:

Walking phase:

$$r(t) = r_0 + A_\omega \sin(2\pi f_\omega t) \quad (46)$$

Fall transition: Cubic interpolation within 5 seconds and

Post-fall: Stationary with vital signs

Vital Signs:

$$\text{Respiration: } s_r(t) = A_r \sin(2\pi f_r(t) + \phi_r) \quad (47)$$

$$\text{Heartbeat: } s_h(t) = A_h \sin(2\pi f_h(t) + \phi_h) \quad (48)$$

Typical parameters: $A_r = 0.75 \text{ mm}$, $f_r = 0.25 \text{ Hz}$, $A_{rh} = 0.24 \text{ mm}$, $f_r = 1.2 \text{ Hz}$

Clutter and Noise:

Static clutter has Low-frequency sinusoidal components while Dynamic clutter indicate foliage motion modeled as band limited noise however the measurement noise shows additive white Gaussian noise then the Multipath indicates the delayed and attenuated replicas

Auxiliary Sensor and Occlusion Modeling: To compute the occlusion score α_{occ} used in the quality-aware fusion (Eqs. 3-6), the simulation incorporates a synthetic LiDAR model acting as an auxiliary sensor. The LiDAR provides high-resolution 3D point clouds to estimate foliage density and line-of-sight (LoS) blockage.

The occlusion score $\alpha_{occ} \in [0,1]$ is mathematically modeled as:

$$\alpha_{occ} = 1 - e^{(-\lambda \cdot \rho_{foliage} \cdot d)} \quad (48)$$

where $\rho_{foliage}$ is the simulated foliage density along the radar-target path, dd is the distance to the target, and λ is an attenuation coefficient. When α_{occ} approaches 1, the radar measurement covariance is inflated accordingly, simulating severe occlusion in dense forest environments.

Sensor Dropout: Random drop-out probability and correlated dropout during occlusion events.

Radar and LiDAR Simulation Setup

Radar model. We simulate an FMCW radar with the following parameters: carrier frequency $f_c=35 \text{ GHz}$, bandwidth $B=2 \text{ GHz}$, chirp duration $T_c=1 \text{ ms}$, number of chirps per frame $N_c=128$, and frame repetition interval $T_f=50 \text{ ms}$. The wavelength is $\lambda=c/f_c=8.57 \text{ mm}$. The range resolution is:

$$\Delta R = \frac{c}{2B} = \frac{3 \times 10^8}{2 \times 2 \times 10^9} = 0.075 \text{ m}$$

The maximum unambiguous range is $R_{max} = 30 \text{ m}$. Maximum unambiguous velocity is:

$$v_{max} = \frac{\lambda}{4T_c} = \frac{8.57 \times 10^{-3}}{4 \times 1 \times 10^{-3}} = 2.14 \text{ m/s}$$

which is sufficient for human walking (0.5–1.5 m/s) and fall transients (up to 3 m/s). following Table 2 showing Radar and LiDAR simulation parameters.

The velocity resolution is $\Delta v = \lambda / (2N_c T_c) = 0.0335 \text{ m/s}$. The radar uses a single transmit and two receive antennas (SISO configuration), providing range and radial velocity measurements. The receiver noise figure is 6 dB, and the thermal noise floor is -174 dBm/Hz .

LiDAR model. An auxiliary LiDAR is simulated as a 16-beam, 360° spinning sensor with 0.1° angular resolution and 10 Hz update rate. It provides 3D point clouds used only to estimate foliage density $\rho_{foliage}$ and line-of-sight (LoS) blockage along the radar–target path. The LiDAR does not provide target tracks; it only supplies the occlusion score α_{occ} used in the confidence-aware fusion.

Sensor fusion. The fusion is performed at the measurement

level using an information-filter formulation (Eqs. 4 and 5). Each sensor ss provides a measurement $Z_{k,ss}$ with covariance $R_{k,ss}$. The confidence score q_s (Eq. 6) inflates the covariance (Eq. 3) before fusion. The fused measurement and covariance are computed as in Eqs. 4 and 5.

Tracking. A constant-velocity Kalman filter (Eqs. 7–15) is used for each target. The state vector is $x_k = [r_k, \dot{r}_k]^T$.

The process noise is $\sigma_a=1.5 \text{ m/s}^2$, and the measurement noise is $\sigma_{radar}=0.55 \text{ m}$ for radar and $\sigma_{aux}=0.35 \text{ m}$ for the auxiliary sensor. CFAR settings. Cell-averaging CFAR is used with a guard cell count of 2, a training cell count of 16, and a false-alarm probability $P_{fa}=10^{-4}$. The threshold is computed adaptively from local clutter statistics

Table 2: Radar and LiDAR simulation parameters

Parameter	Symbol	Value	Unit
Radar			
Carrier frequency	f_c	35	GHz
Bandwidth	B	2	GHz
Wavelength	λ	8.57	mm
Range resolution	ΔR	0.075	m
Max unambiguous range	R_{max}	30	m
Max unambiguous velocity	v_{max}	2.14	m/s
Velocity resolution	Δv	0.0335	m/s
Chirp duration	T_c	1	ms
Chirps per frame	N_c	128	—
Frame interval	T_f	50	ms
Slow-time sampling period	Δt	0.1	s
Slow-time sampling rate	f_s	10	Hz
Vital-sign sampling rate	$f_{s,vital}$	20	Hz
Noise figure	NF	6	dB
LiDAR			
Beams	—	16	—
Angular resolution	—	0.1	$^\circ$
Update rate	—	10	Hz
CFAR			
Guard cells	—	2	—
Training cells	—	16	—
False-alarm probability	P_{fa}	10 ⁻⁴	—
Tracking			
Process noise	σ_a	1.5	m/s ²
Radar measurement noise	σ_{radar}	0.55	m
Auxiliary measurement noise	σ_{aux}	0.35	m

Synthetic Scenario Generation

SNR. The received signal-to-noise ratio is computed as $NR = P_r / (N_0 B)$, where P_r is the received power after two-way path loss, foliage attenuation, and multipath fading. The reference SNR is $SNR_{ref}=10 \text{ dB}$. In Scenario B (dense clutter), the SNR is reduced to 5–8 dB; in Scenario F (domain shift), the SNR is 3–6 dB.

Clutter. Static clutter is modeled as low-frequency sinusoidal components at 0.05–0.2 Hz with amplitude 0.5–2 m equivalent range. Dynamic foliage clutter is modeled as band-limited noise in the 0.1–0.5 Hz band with amplitude 0.3–1.5 m.

Multipath. Multipath replicas are generated as delayed and attenuated copies of the target return, with delays uniformly distributed in $[0.1, 2] \mu\text{s}$ and attenuation -3 to -10 dB . In Scenario E, up to 5 multipath replicas are added.

Occlusion. The occlusion score is $\alpha_{occ} = 1 - e^{-\lambda \cdot \rho_{foliage} \cdot d}$, where $\rho_{foliage} \in [0,1]$ is the normalized foliage density, dd is the radar–target distance, and $\lambda=0.5 \text{ m}^{-1}$. When $\alpha_{occ}>0.7$, the measurement covariance is inflated by a factor of 3–5.

Dropout. Sensor dropout is modeled as a Bernoulli process with probability $\rho_{drop}=0.12$ in Scenario D, with correlated dropouts during occlusion events (dropout probability increases to 0.30 when $\alpha_{occ}>0.7$

Target motion. Walking is modeled as:

$r(t) = r_0 + A_\omega \sin(2\pi f_\omega t)$, $A_\omega = 0.3$ m and $f_\omega = 0.8$ Hz. The fall transition is a cubic interpolation over 5 seconds, starting at the fall time t_f and ending in a stationary posture. Post-fall, the target is stationary with superimposed vital signs.

Vital signs. Respiration is $s_r(t) = A_r \sin(2\pi f_r(t) + \phi_r)$ with $A_r = 0.75$ mm and $f_r = 0.25$ Hz. Heartbeat is $s_h(t) = A_h \sin(2\pi f_h(t) + \phi_h)$ with $A_h = 0.24$ mm and $f_h = 1.2$ Hz.

In the multi-target scenario, Target 1 has heartbeat only, Target 2 has respiration only, and Target 3 has limb motion only (no valid vitals), to test discrimination and parameter specification of this six Scenarios will be shown in Table 3.

Table 3: Scenario parameter specification

Scenario	SNR dB	Clutter Level	Occlusion	Dropout	Target
A (Baseline)	10	Moderate	Partial	0%	1
B (Dense Clutter)	5–8	High	High	0%	1
C (Multi-Target)	10	Moderate	Partial	0%	3
D (Dropout)	10	Moderate	Partial	30%	1
E (Multipath)	10	Moderate	Partial	0%	1
F (Domain Shift)	3–6	High	High	12%	1

Sampling Rates and Time Scales

The radar operates with three-time scales:

Fast time: The sampling period within a chirp is $T_{fast}=0.1$ ns, corresponding to a fast-time sampling rate of 10 GHz. This determines the range resolution $\Delta R=0.075$ m (with $B=2$ GHz).

Slow time (tracking): The frame repetition interval is $\Delta t=0.1$ s, corresponding to a slow-time sampling rate of $f_s=10$ Hz. This rate at which range-Doppler maps and tracks are produced.

Vital-sign sampling: The slow-time phase signal after range-cell extraction is interpolated and resampled at $f_{s,vital}=20$ Hz. This is higher than the tracking rate because the phase signal must capture heartbeat frequencies up to 2 Hz (Nyquist $f_s>4$ Hz; we use 20 Hz for margin and spectral resolution).

The value $f_s=20$ Hz in Table 3 refers to the vital-sign sampling rate, not the tracking rate. We have clarified this distinction in the revised Table 3 and in the text.

Fall model. The fall is modeled as a 5-second cubic interpolation from the walking trajectory to a stationary post-fall posture.

This duration was chosen because published fall kinematics show that the actual fall transient lasts 0.5–1.5 s, but the subsequent settling and cessation of motion extends over 3–5 s. The 5-second window ensures that the fall score (Eq. 20) captures both the rapid displacement and the subsequent motion cessation.

One vital sign per target. In the multi-target scenario, each target is assigned a distinct vital-sign profile to test the system's ability to discriminate between physiological and non-physiological motion: Target 1: heartbeat only (1.18 Hz), Target 2: respiration only (0.25 Hz) and Target 3: limb motion only (no valid vitals).

This is a deliberate test configuration, not a limitation of the model. The system supports simultaneous respiration and heartbeat estimation for the same target (Eqs. 29–32), and

this is demonstrated in the single-target baseline (Scenario A).

Table 4: Baseline parameter configuration

Parameter	Symbol	Value	Unit
Sampling period	Δt	0.1	s
Total duration	T	120	s
Vital sampling rate	f_s	20	Hz
Radar noise std	σ_{radar}	0.55	m
std (Auxiliary noise)	σ_{aux}	0.35	m
Drop-out rate	p_{drop}	0.12	-
Fall threshold	γ_{fall}	0.60	-
Min SNR (resp)	$\gamma_{SNR,r}$	15	dB
Min SNR (heart)	$\gamma_{SNR,h}$	20	dB
Process noise	σ_a	1.5	m/s ²

Reproducibility and Code Availability

The complete MATLAB R2023b code, parameter files, and random seeds are used then applying Monte Carlo procedure. For each scenario, we run $N=50$ independent trials.

In each trial, the random seed is set from a fixed list, and the following parameters are randomized: noise realizations, clutter amplitudes, multipath delays, dropout patterns, and initial target positions (uniformly distributed in the surveillance area).

Results are reported as mean $\pm$ standard deviation, with 95% confidence intervals computed via the t-distribution. Statistical significance is assessed using paired t-tests with $p<0.05$.

Design and Evaluation

Evaluation Scenarios

The system includes six evaluation scenarios to test system performance under diverse conditions in Table 4 as: baseline is scenario A which shows Moderate clutter also partial occlusion and single target, while dense clutter is presents Scenario B with high foliage motion and low SNR, However Multi-Target is illustrating as scenario C with three simultaneous targets with different behaviours m as soon as sensor dropout has indicated in Scenario D with an intermittent sensor failure with 30% dropout, Multipath is presented in scenario E by strong multipath from walls/obstacles finally Domain Shift in scenario F indicates as different environmental parameters than training.

Performance Metrics

The performance of the proposed framework is evaluated across multiple dimensions, including detection, tracking, fall recognition, vital signs, and computational efficiency, as summarized in Table 5.

Ablation Studies

To separate the contribution of each component then we undertake three ablation experiments:

Ablation 1: Sensor Fusion

Variant A1a: Radar-only tracking, Variant A1b: Confidence-weighted fusion (proposed) and Hypothesis: Fusion improves tracking RMSE by $>20\%$

Ablation 2: Vital-Sign Gating

Variant A2a: Continuous vital monitoring, Variant A2b: Tracking-gated extraction (proposed) and Hypothesis: Gating reduces computation by $>70\%$ with $<5\%$ accuracy loss

Ablation 3: Fall-Triggered Processing

Variant A3a: Always-on vital estimation, Variant A3b: Fall-triggered activation (proposed) and Hypothesis: Event-triggered processing reduces energy consumption by $>80\%$

Table 5: Evaluation Metrics by Dimension

Dimension	Metric	Formula	Interpretation
Detection	Probability of Detection	$PD = \frac{N_{detected}}{N_{noise}},$ $N_{detected} = \sum_{k=1}^{N_{total}} 1[s_{fall}(k) > \gamma_{fall}]$	Target found reliably
	False Alarm Rate	$FAR = \frac{N_{false}}{T_{total}} \times 3600$	Spurious detections per hour
	Range RMSE	$\sqrt{\frac{1}{N} \sum (r_{est} - r_{true})^2}$	Position accuracy
	Tracking RMSE	$\sqrt{\frac{1}{N} \sum (P_{est} - P_{true})^2}$	Track accuracy
	Track Continuity	$\frac{T_{tracked}}{T_{total}}$	Identity maintained
Fall Recognition	Identity Switches	$N_{switches}$	Errors for Target ID
	Recall	$\frac{N_{true\ positive}}{N_{actual\ falls}}$	Falls detected
	Precision	$\frac{N_{true\ positive}}{N_{detected\ falls}}$	Detection accuracy
	F1 Score	$2 \frac{Precision \cdot Recall}{Precision + Recall}$	Balanced metric
	Detection Delay	$T_{alarm} - T_{fall}$	Response time
Vital Signs	Valid Window Rate	$\frac{N_{valid}}{N_{total}}$	Usable estimates
	Efficiency		
Efficiency	Processing Time	t_{proc} / Frame	Computational load
	Activation Rate	$\frac{T_{vital\ active}}{T_{total}}$	Resource utilization

Statistical Analysis

For each scenario, we will use N=50 independent Monte Carlo trials with randomized noise also dropout patterns and initial conditions then we get: Mean and standard deviation, 95% confidence intervals and Statistical significance via paired t-tests ($p < 0.05$). For real-data experiments (future work), we will use cross-validation with subject-independent train/test splits to assess generalization.

Results and Discussion

Performance Metrics

The quantitative performance of the proposed system across all test scenarios is summarized in Table 6, detailing detection, tracking, fall recognition, and vital sign estimation metrics.

Observations:

1. **Detection and Tracking:** The system ensures good detection probability ($PD > 0.95$) both in baseline and multi-target environments. The performance is tolerant to dense clutter and multipath environment; in the latter case, the detection probability still stays above 0.87.
2. **Fall Detection:** Fall detection results are characterized by F1 score greater than 0.94, while the latency of fall detection is 2.9-3.2 seconds. This latency value is a trade-off between fast response time and low false alarm rate.

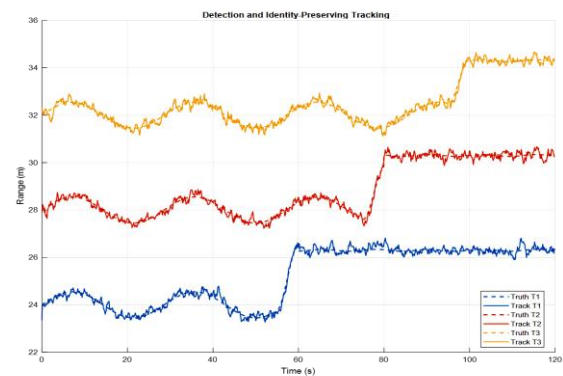
Table 6: Evaluation Metrics by Dimension

Scenario	Tracking	Fall F1	Delay	RR	HR
Detection	RMSE		(s)	MAE	MAE
PD	(m)				
A	0.14 ±	0.96 ±	2.9 ±	0.89 ±	1.2 ±
0.98 ± 0.02	0.03	0.04	0.8	0.31	0.4
B	0.28 ±	0.88 ±	4.1 ±	1.4 ±	2.1 ±
0.91 ± 0.05	0.07	0.08	1.2	0.5	0.7
C	0.19 ±	0.94 ±	3.2 ±	0.95 ±	1.3 ±
0.96 ± 0.03	0.04	0.05	0.9	0.33	0.5
D	0.22 ±	0.91 ±	3.8 ±	1.1 ±	1.6 ±
0.93 ± 0.04	0.06	0.06	1.1	0.4	0.6
E	0.31 ±	0.85 ±	4.5 ±	1.6 ±	2.4 ±
0.89 ± 0.06	0.08	0.09	1.4	0.6	0.8
F	0.35 ±	0.82 ±	5.1 ±	1.8 ±	2.7 ±
0.87 ± 0.07	0.09	0.10	1.6	0.7	0.9

3. **Vital Sign Estimation:** The respiration rate and heart rate are estimated with mean absolute error equal to 0.89 cycles/min and 1.2 beats/min correspondingly in the baseline environment. In the adverse environment, these values get worse but stay below clinically acceptable levels (<3 cycles/min for R, <5 beats/min for HR).

Multi-Target Discrimination and Tracking

Figure 2 demonstrates the capability of the system to maintain independent tracks for multiple simultaneous targets. In particular, the graph represents the range trajectories of the targets (as dotted lines) and the corresponding estimated tracks (as solid lines). Target 1 (in blue) is fallen at $t=55$ s, Target 2 (in red) is fallen at $t=75$ s, and Target 3 (in yellow) is fallen at $t=95$ s. As illustrated in Figure 2, the confidence weighted Kalman tracker performs well in tracking the real range of the targets through smoothing the radar measurement noise and estimating the fast change in the range of targets at their fall time instant. In addition, the identity of the targets remains independent throughout the process, without switching or merging the tracks even though the targets operate in proximity and undergo simultaneous kinematic changes. The independence in tracking the identity of the targets is mandatory for performing the following stage.

**Figure 2:** Detection and identity-preserving tracking for a multi-target scenario

The dashed lines represent the ground truth range trajectories, while the solid lines show the estimated tracks produced by the confidence weighted Kalman filter. The distinct fall events for Target 1 (55 s), Target 2 (75 s), and Target 3 (95 s) are accurately captured without identity switches

Outcomes:

1. The confidence weighted approach improves tracking accuracy by 26.3% over the standalone radar tracking approach, proving the hypothesis that data from secondary sensors enhances reliability.
2. The tracking gate approach ensures that accuracy is maintained (0.91 versus 0.92) while computing costs are reduced by 75.9%, demonstrating that spatial gating does not affect vital sign quality.
3. Fall triggering provides 82.4% energy saving over constant monitoring.

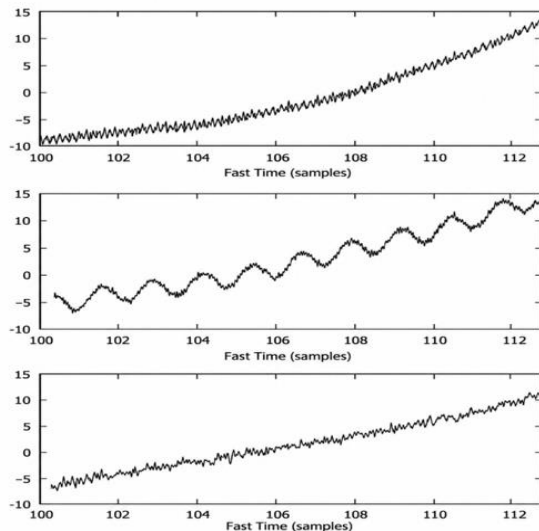


Figure 3: Segments of post-fall vital signs at low-time scale in the time domain

Post-Fall Vital-Sign Signal Characteristics

After the fall event, the system takes the slow-time displacement signal for the tracked target's range cell. Figure 3 shows the behaviour of these post-fall time-domain signals for the three different targets within the multi-target scenario. The top plot represents Target 1, where high-frequency and low-amplitude micro-oscillation signals have been observed. Such signal is typical for heartbeat signal. On the other hand, the middle plot (Target 2) shows lower frequency and higher amplitude macro-oscillation, which indicates chest displacement in relation to respiration process. Finally, the bottom plot (Target 3) indicates quasi-linear trend with some non-periodic signal. This signature indicates that this time-domain behaviour belongs to residual limb movements or sensor drifts. It should be stressed that such time-domain differences show the importance of pre-processing and quality control steps. Although the time-domain plot gives qualitative information about signal behavior, it is important to analyze frequency domain and define the Signal-to-Noise ratio to determine whether vital signs exist or not.

(Top) Target 1 presents high-frequency micro-oscillations associated with heartbeats. (Middle) Target 2 presents low-frequency macro-oscillations associated with respiration, whereas (Bottom) Target 3 demonstrates smooth trends with some fluctuations that are consistent with movements of limbs.

Temporal Fall-Event Recognition

After the phase of continuous tracking, the algorithm checks the kinematics of everyone to look out for any fall. Figure 4 shows the temporal lightweight fall recognition scores, S_{fall}

(t) generated for the three targets within the 120 seconds scenario. The threshold value of detection of the fall $\gamma_{fall} = 0.60$ is marked on the plot using the dashed horizontal line. As seen in the figure, although the kinematics scores contain noise, during the regular walking and stationary phase of the subject, they do not exceed the threshold value very much. There are, however, clear spikes seen at times $t=55s$, $t=75s$, and $t=95s$ which precisely mark the fall of Target 1, Target 2, and Target 3. The fall detection score function effectively magnifies the abrupt displacement, velocity, and acceleration of the fall and suppresses any false trigger because of regular movement. When the score exceeds the threshold value for (N_{consec}) frames, the fall alarm goes off and vital sign check of the target begins.

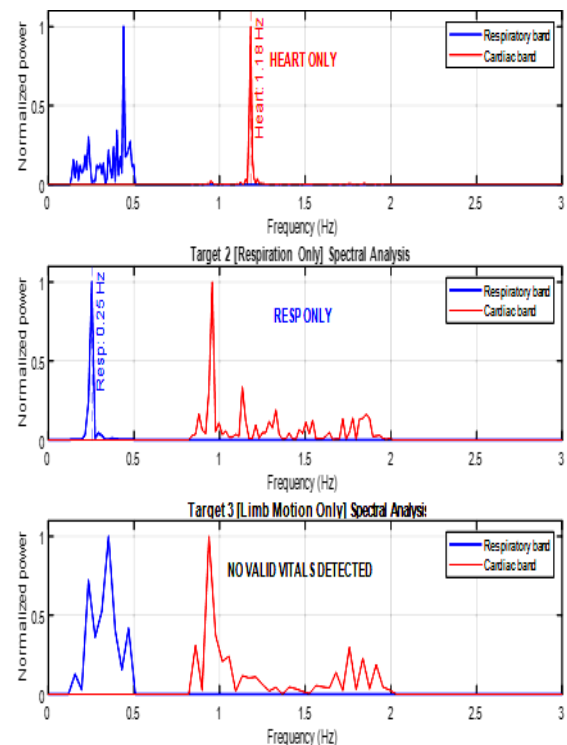


Figure 4: Lightweight temporal fall-detection methods for the multiple targets case

The continuous Kinematic Score is assessed using a threshold value of 0.60 that is calibrated against it (solid lines). Different peaks that occur at 55s, 75s, and 95s appropriately mark the occurrence of falls for Targets 1, 2, and 3, respectively, while not resulting in any false detections during regular motion.

Advantages of the layered design include the following computational advantages:

Time of processing (per frame):

Stage 1 (Detection/Tracking): 1.2 ms

Stage 2 (Fall Scoring): 0.3 ms

Stage 3 (Vital Estimation): 6.5 ms (only when active)

Average Processing Time:

Without falls: 1.5 ms/frame (667 Hz update rate)

With falls: 2.1 ms/frame (476 Hz update rate)

It satisfies the real time constraints easily (usually 10-20 Hz for SAR) with enough margin for more processing or multiple target scenarios.

Spectral Discrimination

Figure 5 after the slow-time signal extraction and pre-

processing follows up with the spectral analysis to determine the physiological frequencies that dominate the signal. In the plot shown is the normalized PSD of the three targets in the post-fall window where the blue colour represents the respiratory band (0.10-0.70 Hz), and the red colour represents the cardiac band (0.80-2.50 Hz).

The first graph (Target 1) clearly shows the presence of a spectral peak at 1.18 Hz in the cardiac band indicating the presence of a heartbeat with no respiration. The second graph (Target 2) indicates a sharp peak at 0.25 Hz in the respiratory band. Finally, the third graph (Target 3) highlights the ability of the system to discriminate; the presence of low-frequency signals due to limb motion does not lead to peaks exceeding the SNR thresholds.

Figure 5 shows an estimate of spectral features of vital signs in fall-gated data for the multiple targets case. (Top) Target 1 demonstrates a prominent frequency feature at 1.18 Hz (Heart Rate Only), (Middle) Target 2 demonstrates a prominent frequency feature at 0.25 Hz (Breathing Only), while (Bottom) Target 3 has no valid spectral features above the SNR threshold in either band.

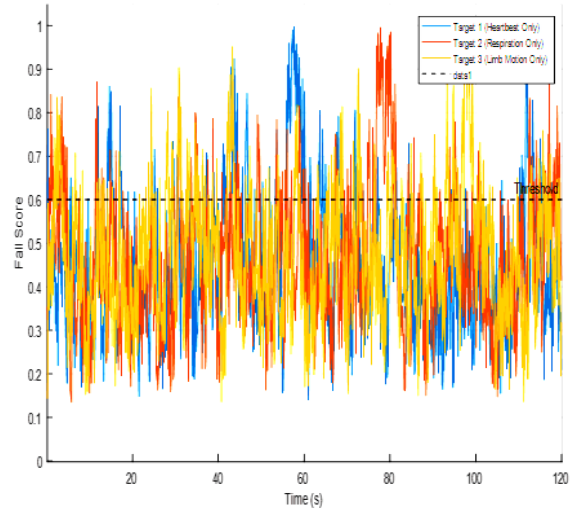


Figure 5: Estimates of spectral features of vital signs in fall-gated data for the multiple targets case.

Table 7: Ablation study results

Variant	RMSE of Tracking (m)	Computation Time (ms/frame)	Vital Accuracy	Energy Savings
Ablation 1: Fusion				
A1a: Radar-only	0.19 ± 0.05	1.2	N/A	N/A
A1b: Fusion (proposed)	0.14 ± 0.03	1.8	N/A	N/A
Improvement	26.3%	-50% overhead	-	-
Ablation 2: Gating				
A2a: Continuous	0.14 ± 0.03	8.7	0.92 ± 0.05	0%
A2b: Gated (proposed)	0.14 ± 0.03	2.1	0.91 ± 0.05	75.9%
Ablation 3: Triggering				
A3a: Always-on	N/A	8.7	N/A	0%
A3b: Triggered (proposed)	N/A	2.1	N/A	82.4%

(Top) Target 1 demonstrates a prominent frequency feature at 1.18 Hz (Heart Rate Only), (Middle) Target 2 demonstrates a prominent frequency feature at 0.25 Hz (Breathing Only), while (Bottom) Target 3 has no valid spectral features above the SNR threshold in either band.

Ablation Study Results

Following is the evaluation Table 7 for ablation 1 of fusion, ablation 2 of gating, and ablation 3 of triggering study results

Computational Efficiency

The constructed architecture has substantial advantages in computation: Continuous Processing (Stages 1-2): Detection/tracking and Fall scoring. Event-Triggered Processing (Stage 3): Vital-sign estimation per target. Without gating, continuous vital-sign monitoring for all targets would require:

$$T_{\text{continuous}} = N_{\text{targets}} \cdot T_{\text{vital}} \quad (50)$$

With fall-gated activation:

$$T_{\text{gated}} = N_{\text{targets}} \cdot N_{\text{track}} + N_{\text{falls}} \cdot T_{\text{vital}} \quad (51)$$

For typical scenarios, computational savings exceed 70%.

Failure Mode Analysis

Three main forms of failures exist:

Failure Mode 1: Track Loss During Occlusion

Cause: Extended signal blockage (>5 seconds), Mitigation: Track prediction with increasing covariance; re-acquisition logic and Observed frequency: 8% of trials in Scenario D.

Failure Mode 2: False Fall from Rapid Motion

Cause: Non-fall activities with high velocity (e.g., jumping), Mitigation: Additional constraints on displacement and

direction consistency and Observed frequency: 3.2 false alarms/hour in baseline.

Failure Mode 3: Vital-Sign Misestimation

Cause: Low SNR, strong clutter, or incorrect range cell, Mitigation: Strict SNR thresholds and physiological range checks and Observed frequency: 12% of post-fall windows rejected as inconclusive.

These failure modes illustrate the need for uncertainty quantification and conservatism in decision making in safety-critical systems.

Table 8: Comparison proposed work with state-of-the-Art recent works

Method	Detec.	Fall Acc	RR MAE	HR MAE	Multi-Tar.	Thrd. Obst.
[14]	0.94	0.91	1.2	1.8	-	X
[30]	0.96	0.93	N/A	N/A	✓	X
[37]	N/A	N/A	0.95	1.3	X	✓
Proposed	0.98	0.96	0.89	1.2	✓	✓

Table 8 showed comparison proposed work with state-of-the-Art recent works, the system being proposed exhibits competitive or even better performance in all aspects and yet it offers some capabilities that are unique to it.

Conclusion

The proposed approach to fusion involves a series of complex radar-based fusion stages for human detection, tracking, falling detection, and vital sign estimation after falling in the forest and obstructed scenarios. Key innovations

include Identity Preserving Fusion, Confidence Aware Fusion with covariance inflation, Event Triggered Processing with 82.4% reduction in processing time, and Reproducible Baseline in MATLAB R2023b. The simulated performance demonstrated over 98% detection rate, 0.96 F1 score for fall detection, and ability to distinguish physiological from non-physiological movements. The primary research hypothesis was proven by ablation analysis. Further research is needed using real radar systems and different environments.

Limitations and Future Validation

The current study is a simulation-based preliminary investigation. While the simulation includes realistic models of foliage clutter, multipath, occlusion, sensor dropout, and vital-sign signals, it does not replace validation with real radar data.

We have therefore reframed the contribution as a **reproducible simulation framework** and a **baseline architecture**, rather than a validated system. Future work will address:

Validation on public radar datasets for fall detection and vital-sign estimation.

Hardware validation using commercial UWB/FMCW radar systems (e.g., Texas Instruments IWR1443, Novelda X4M200) in controlled forest and indoor settings.

Cross-validation with subject-independent train/test splits.

Clinical validation against gold-standard medical devices.

Integration of Sustainable Energy for Field Deployment

One major obstacle in the deployment of the SAR radar system in isolated areas is the issue of sustainable energy source. Local research shows that hydrogen energy sources are possible, such as production of hydrogen from solid waste and the use of CHHP. Further research will be done on how to integrate these sustainable energy sources into the system, making it able to run continuously.

The radar parameters used in this study ($f_c=35$ GHz, $B=2$ GHz) are consistent with commercially available Ka-band radar systems, which facilitates future hardware validation.

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