

Assessing Sensing Quality of mmWave-Based Vital Sign Monitoring: An A-Priori Approach

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Abstract. Millimeter-wave (mmWave) radar signals enable contactless, high-resolution vital sign sensing. However, their inherent characteristics—strong directionality and short wavelength—make reflected signals highly sensitive to minor geometric variations, leading to significant fluctuations in sensing quality. This issue is particularly critical in mobile sensing scenarios such as embodied AI, where robots must proactively select optimal sensing positions and orientations. Existing studies are inadequate in this setting, as they are either a-posteriori, requiring data acquisition, or designed for other technologies such as Wi-Fi. To address this, we propose the Vital Sign Sensing Index (VSSI), an a-priori metric that leverages pre-measurable spatial and environmental features for mmWave vital sign monitoring. Additionally, we derive a frequency-domain a-posteriori formulation tailored to this context to compute ground-truth sensing quality for validation. Experimental results show that VSSI achieves a Spearman correlation of 0.912 with ground truth and reduces heart rate (HR) estimation error by up to 50% compared to intuitive distance-orientation selection strategies.

Keywords: Sensing quality · mmWave · vital sign.

1 Introduction

mmWave technology has gained increasing attention in wireless sensing due to its high spatial resolution [8] and ability to penetrate non-metallic materials. It also enables contactless vital sign monitoring [10], making it well-suited for continuous in-home healthcare.

However, the short wavelength and strong directionality of mmWave signals make reflections highly sensitive to geometric variations, leading to significant fluctuations in sensing quality. This is particularly critical in mobile sensing scenarios like embodied AI, where mobile robots must optimize sensing poses.

As illustrated in Fig. 1, real-world environments impose practical constraints: furniture may block line-of-sight (LoS) or limit positions, reducing signal quality. Consequently, robots must select from a constrained set of LoS-clear positions



Fig. 1: Multiple reachable sensing positions in a home environment.

with varying distance and orientation, resulting in a complex spatial decision space. For example, location A, which is farther and obliquely oriented, yields lower sensing quality than location B, which is closer and directly facing the chest. Such constraints are often overlooked in controlled laboratory settings.

An intuitive approach for location selection is to use Signal-to-Noise Ratio (SNR), but it is designed for communication systems and fails to capture sensing-specific characteristics. Moreover, as an a-posteriori metric, it requires prior data acquisition, making it unsuitable for proactive decisions.

Recent works on radar-based vital sign monitoring focus on post-acquisition signal processing to enhance the extraction of weak physiological signals [9, 24].

Several studies have also explored signal quality metrics for mmWave sensing [3, 7, 25]. However, these approaches are predominantly a-posteriori, relying on acquired data for evaluation. As a result, effective a-priori quality metrics for mmWave-based vital sign monitoring remain largely unexplored.

Meanwhile, emerging research on sensing quality modeling in wireless systems highlights the importance of spatial factors. For example, WiFi-based works [12, 21] analyze geometric effects and guide device placement. However, these methods are tailored to long-wavelength systems, where weak directionality and constant RCS assumptions hold—conditions that do not apply to mmWave sensing. In addition, they focus on motion-related tasks rather than vital sign monitoring.

In this paper, we propose the Vital Sign Sensing Index (VSSI), an a-priori metric that predicts sensing quality from pre-measurable spatial and environmental features for mmWave vital sign monitoring. VSSI is based on the insight that signal strength is governed by deterministic physical structures rather than purely stochastic factors. While certain interferences (*e.g.*, vibrating objects) are difficult to model a-priori, they have negligible impact on the relative ranking across distance–orientation combinations and can thus be omitted during position selection. Nevertheless, this formulation introduces several key challenges.

Signal Mixing and Intractability. In realistic environments, severe signal mixing prevents isolating individual power components. This makes conventional metrics (*e.g.*, SNR) inapplicable, as static reflections, dynamic interference, and noise are inextricably coupled.

Uncertainty in RCS under Varying Sensing Angles. Unlike WiFi, mmWave reflectivity varies significantly with orientation, invalidating the constant RCS assumption and requiring explicit modeling.

To address these challenges, we first define Sensing Quality (SQ) and derive its a-posteriori frequency-domain formulation. We then propose VSSI as an a-priori approximation by modeling key geometric factors, including distance and orientation. In particular, we estimate orientation-dependent RCS via effective thoracic projection area and an orientation correction function, enabling accurate SQ prediction across different distance-orientation combinations.

Our main contributions are summarized as follows:

- To the best of our knowledge, this work is the first to model an a-priori SQ quantification metric (VSSI) for mmWave vital sign monitoring. We employ Gaussian Process Regression to model orientation correction, combining it with distance and orientation to predict SQ before data acquisition.
- We rigorously derive the frequency-domain a-posteriori formulation of SQ for mmWave vital sign monitoring and experimentally validate its strong correlation with actual sensing accuracy.
- Extensive experiments demonstrate that the a-priori metric VSSI consistently ranks sensing locations in alignment with the ground-truth SQ, achieving a Spearman correlation of 0.912. When applied to HR estimation, VSSI outperforms distance-only and orientation-only baselines, reducing estimation error by 23% and 50%, respectively.

The paper is organized as follows: Sec. 2 reviews the related work, while Sec. 3 provides the necessary theoretical background. Sec. 4 formally defines SQ in the frequency domain. Sec. 5 details the a-priori VSSI metric modeling. Sec. 6 evaluates the implementation, and Sec. 7 concludes the paper.

2 Related Work

mmWave-Based Vital Sign Monitoring. mmWave sensing has gained increasing attention across various applications [4, 26, 27]. Owing to its submillimeter motion sensitivity, it shows strong potential for contactless vital sign monitoring [2, 16, 17, 19, 22]. However, prior works mainly focus on post-acquisition signal processing for extracting HR and respiration. In contrast, We address the complementary problem of selecting sensing positions that yield higher-quality signals *a-priori*. Our approach is compatible with the existing signal processing methods and can further enhance overall performance. Since HR is more challenging to detect than respiration, we adopt HR monitoring as the primary evaluation task.

A-Posteriori Signal Quality Quantification. Signal quality assessment has been studied in various contexts. For example, Guo *et al.* [3] and Jiang *et al.* [7] proposed VSNR for vibration sensing based on IQ-domain analysis and noise modeling. Gao *et al.* [1] introduced a noise-motion phase ratio for Wi-Fi gesture recognition, while Zhang *et al.* [25] proposed the VI metric for multi-carrier

signal quality evaluation. However, these methods are inherently *a-posteriori*, relying on features (*e.g.*, SNR, spectral entropy) extracted from *already acquired* data. This leads to a trial-and-error process, where quality is assessed only after data acquisition, limiting proactive decision-making.

In contrast, we propose an *a-priori* metric that predicts sensing quality from spatial and environmental features before data acquisition, enabling proactive selection of optimal sensing locations and reducing unnecessary exploration costs.

A-Priori Signal Quality Quantification. Prior works have explored a-priori metrics for RF sensing, particularly in Wi-Fi applications such as coverage optimization [21] and velocity estimation [12]. These models, however, are tailored to Wi-Fi's long-wavelength regime, where strong diffraction and multipath justify treating target RCS as a constant approximation.

In contrast, we consider mmWave-based HR monitoring, which operates under fundamentally different conditions. The short wavelength leads to highly directional propagation and a dominant signal path, making orientation-dependent RCS variations non-negligible. As a result, RCS becomes a first-order factor in signal quality, unlike its simplified treatment in Wi-Fi sensing. This necessitates a new a-priori model that explicitly incorporates RCS.

3 Background

Basic Signal Modeling. In FMCW mmWave radar, received signals (Fig. 2) typically include: (1) static clutter x_s from stationary surfaces; (2) target signal $x_{\text{tar}}(t)$ reflecting physiological micro-motions; (3) interference $x_i(t)$ from unrelated sources; and (4) additive thermal noise $x_n(t)$.

Following homodyne mixing, the radar yields the intermediate frequency (IF) signal that retains the components' amplitude and phase information. The resulting formulation serves as the basis for characterizing SQ:

$$\begin{aligned} x_{\text{IF}}(t) &= x_{\text{tar}}(t) + x_s(t) + x_i(t) + x_n(t) \\ &= A_{\text{tar}}(t)e^{-j\phi_{\text{tar}}(t)} + A_s(t)e^{-j\phi_s(t)} + A_i(t)e^{-j\phi_i(t)} + A_n(t)e^{-j\phi_n(t)}, \end{aligned} \quad (1)$$

where A_i and ϕ_i denote the amplitude and phase of each component $x_j(t)$, with $j \in \{\text{tar}, s, i, n\}$.

Conventional SNR. As a fundamental metric in communication systems, SNR is proportional to the received power P_r , assuming a constant noise floor. In ideal free space, P_r follows the radar equation [15]: $P_r = \frac{P_t G^2 \lambda^2 \sigma}{(4\pi)^2 d_r^4}$, where P_t, G, λ, d_r , and σ denote transmit power, antenna gain, wavelength, distance, and RCS, respectively.

For tractability, prior studies [12, 21] often assume a constant RCS (σ), reducing SNR to a function of distance d_r alone. However, this simplification overlooks the anisotropic reflectivity of human bodies. In practice, orientation heavily influences signal strength, as a distant subject facing the radar can yield stronger reflections than a closer one at an unfavorable angle. Thus, distance d_r

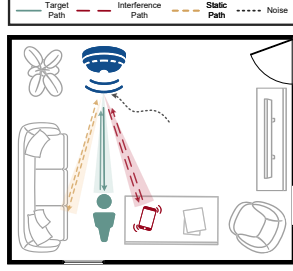
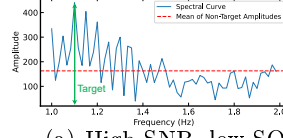
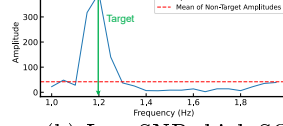


Fig. 2: mmWave propagation includes target reflection, static clutter, interference, and noise.



(a) High SNR, low SQ



(b) Low SNR, high SQ

Fig. 3: Comparison of SNR and SQ.

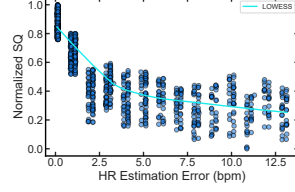


Fig. 4: Correlation between a-posteriori SQ and HR estimation error.

alone cannot reliably capture signal quality variations. Furthermore, the conventional SNR definition [18] assumes all received components contribute positively: $\text{SNR} = |x_{\text{tar}}(t) + x_s(t) + x_i(t)|^2 / |x_n(t)|^2$, where the numerator contains not only the desired physiological signal $x_{\text{tar}}(t)$, but also static clutter $x_s(t)$ and dynamic interference $x_i(t)$ from unrelated sources. While appropriate in communication contexts where all components may convey information, this formulation is unsuitable for HR monitoring, where only $x_{\text{tar}}(t)$ is informative and the remaining terms degrade sensing quality.

Moreover, SNR is inherently an a-posteriori metric, computable only after signal acquisition. This limits its use for pre-acquisition decisions, such as selecting an optimal sensing location. Hence, a new signal quality metric is required—one aligned with sensing objectives and predictable prior to data collection.

4 An A-Posteriori Model of Sensing Quality

4.1 Theoretical Definition of Sensing Quality

Unlike communication systems where most received energy is considered useful, sensing relies primarily on dynamic target reflections. Consequently, the communication-centric SNR metric is ill-suited for evaluating sensing performance. In sensing environments, the target signal is often obscured by static clutter, dynamic interference, and thermal noise—collectively hindering information extraction. To better evaluate sensing performance under these conditions, we formulate the SQ [21] metric as:

$$\text{SQ} = \frac{P_{\text{tar}}}{P_s + P_i + P_n} = \frac{|x_{\text{tar}}(t)|^2}{|x_s(t) + x_i(t) + x_n(t)|^2}, \quad (2)$$

where P_j denotes the power of component $x_j(t)$ for $j \in \{\text{tar}, \text{s}, \text{i}, \text{n}\}$. Here, the numerator represents the desired target signal, while the denominator aggregates static clutter, interference (*e.g.*, vibration), and thermal noise.

Fig. 3(a) illustrates high signal power can yield high SNR, yet SQ remains low when interference masks the target. Conversely, Fig. 3(b) shows prominent target dynamics can enhance SQ and sensing performance even at lower SNR. This contrast underscores high SNR does not guarantee sensing effectiveness. By isolating task-relevant dynamics, SQ provides a more robust measure for real-world sensing.

4.2 Derivation of the Computable Form

While Eq. (2) defines SQ in principle, direct computation is infeasible due to signal entanglement and instantaneous instability. To derive a robust, time-averaged estimator, we assume non-target components (clutter, interference, and noise) are mutually uncorrelated, causing their cross-correlations to average to zero. Following Parseval's theorem [13], we transition to the frequency domain via Discrete Fourier Transform (DFT). Assuming spectral separability, the target energy concentrates at a specific index k_{tar} , while non-target energy spans the remaining spectrum.

We identify k_{tar} via a synchronized Polar H10 chest strap for ground truth. This dependency applies only to metric validation, as our a-priori VSSI operates independently. The computable SQ is formulated as:

$$\text{SQ} \approx \frac{|X[k_{\text{tar}}]|^2}{\sum_{k \neq k_{\text{tar}}} |X[k]|^2}, \quad (3)$$

where $X[k]$ is the signal spectrum. As shown in Fig. 4, SQ strongly correlates with HR estimation error ($r = -0.8812$), validating its suitability for evaluation.

5 An A-Priori Metric: Vital Sign Sensing Index Modeling

5.1 Target-Induced Signal Power

The ideal received signal power follows the radar equation [15]. In practice, target orientation can significantly affect return power, so we modify the classical model as follows:

$$P_{\text{tar}} = \omega(\theta) \cdot \frac{P_t G^2 \lambda^2 \sigma(\theta)}{(4\pi)^2 d_r^4}, \quad (4)$$

where θ is the orientation angle, defined as the angle between the human target's facing direction and the direction opposite to the radar beam. As illustrated in Fig. 5, the target is positioned at the center of a circular region, with dashed arrows indicating example orientations θ_1 and θ_2 . By definition, $0 \leq \theta < 2\pi$.

In this equation, the orientation-dependent RCS $\sigma(\theta)$ is approximated by the effective projected area of the human chest:

$$\sigma(\theta) = \begin{cases} D_{\text{chest}} \cdot L_{\text{chest}} & \text{if } \theta = 90^\circ \text{ or } \theta = 270^\circ \\ W_{\text{chest}} \cdot L_{\text{chest}} \cdot \cos \theta & \text{otherwise} \end{cases}, \quad (5)$$

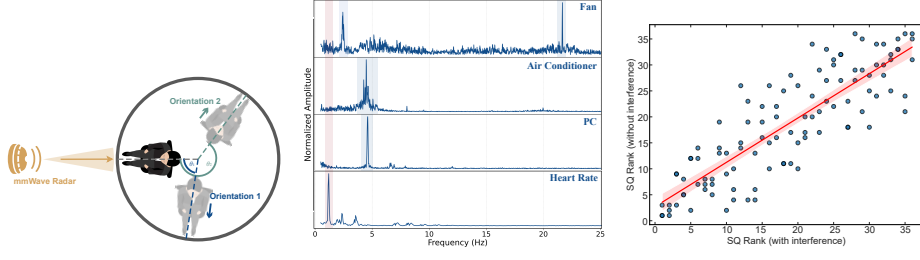


Fig. 5: Top-down view of human orientation θ relative to the radar beam. Fig. 6: Normalized frequency spectra of HR signals and typical indoor interference. Fig. 7: Spearman correlation of SQ rankings with and without interference.

where D_{chest} , W_{chest} , and L_{chest} denote chest depth, width, and longitudinal length. This provides a coarse estimate of RCS based on both body geometry and orientation. However, this approach assumes a homogeneous reflector and captures only the aggregate signal intensity, thereby overlooking internal physiological complexities like tissue depth variation, rib cage occlusion, and heart orientation, all of which exert a non-trivial influence on the returned signal.

To address this, we introduce a physiological correction factor $\omega(\theta)$ in Eq. (4). Unlike macroscopic RCS, $\omega(\theta)$ captures anisotropic coupling between the radar signal and internal cardiac motion, including heart-to-chest-wall distance, tissue attenuation, and rib cage occlusion.

We model the mapping $\theta \mapsto \omega(\theta)$ as a function $f(\theta)$ using Gaussian Process Regression (GPR) [14]. To incorporate physical priors, we adopt a composite kernel rather than a black-box model, and assume $f(\theta) \sim \mathcal{GP}(0, k(\theta, \theta'))$, where

$$k(\theta, \theta') = \sigma_p^2 \exp\left(-\frac{2 \sin^2(\pi(\theta - \theta')/p)}{l_p^2}\right) + \sigma_r^2 \exp\left(-\frac{(\theta - \theta')^2}{2l_r^2}\right) + \sigma_n^2 \delta_{\theta\theta'} \quad , \quad (6)$$

Here, σ_p^2 , l_p , and p denote the variance, length scale, and period of the periodic kernel; σ_r^2 and l_r denote the variance and length scale of the RBF kernel; and σ_n^2 is the noise variance. These terms capture angular periodicity, smooth orientation-specific deviations, and amplitude noise.

Kernel parameters are learned from ground-truth $\omega(\theta)$, defined as $\omega(\theta) = A(\theta)/A(0^\circ)$, where $A(\theta)$ is the measured signal amplitude at orientation θ , normalized by the amplitude when the target faces directly toward the radar. Among the VSSI components, only $\omega(\theta)$ is data-driven; it is calibrated from normalized amplitudes over orientations, without requiring HR estimation or a-posteriori SQ at candidate positions.

5.2 Noise Power

The noise power P_n sets the system sensitivity floor. Although rooted in thermal noise, its practical level is primarily determined by active receiver components.

Accordingly, we adopt a system-level model based on the receiver noise figure F_{sys} , typically specified in front-end datasheets. The equivalent noise temperature is $T = T_0(F_{\text{sys}} - 1)$, where $T_0 = 290$ K. The noise power is then given by $P_n = kTB$, where k is the Boltzmann constant and B is the effective noise bandwidth, usually determined by the baseband filter.

5.3 Dynamic Interference Power

Dynamic interference power P_i , arising from sources such as vibrating appliances, can degrade mmWave radar signals. However, under the considered conditions, its impact is spectrally and functionally negligible for a-priori sensing position selection. This is supported by preliminary experiments.

Operational Context. We consider a typical indoor scenario with three constraints: (i) short-range sensing (≤ 2.5 m), (ii) a narrow-beam mmWave radar directed at the chest, and (iii) a clear LoS.

Spectral Separability. Physiological signals (respiration, HR) are quasi-periodic and concentrated in low-frequency bands. For instance, $f_{\text{HR}} \in [1, 2]$ Hz [28]. In contrast, common indoor interferers (*e.g.*, fans, compressors, motors) operate at higher frequencies (*e.g.*, 5–25 Hz). As shown in Fig. 6, their spectra are largely separated, resulting in minimal interference with HR extraction.

Relative Task Invariance. Our goal is to evaluate *relative* SQ across candidate positions rather than absolute values. Off-beam interferers introduce a near-uniform noise floor across positions, which does not affect relative ranking of VSSI. Experiments with and without a vibrating source yield a Spearman correlation of 0.8536 (Fig. 7), confirming negligible impact on ranking.

Model Simplification. Therefore, we omit the explicit P_i term in the a-priori SQ model, allowing focus on dominant position-dependent factors.

5.4 Putting All Together

Building on the signal components in Sec. 5.1-5.3, we construct an a-priori sensing quality metric VSSI, as a predictor for optimal monitoring positions.

Since the static component can be removed via filtering, it is excluded from the numerator. Starting from the signal power ratio, we approximate:

$$\text{VSSI}' = \frac{P_{\text{tar}}}{P_s + P_i + P_n} \approx \omega(\theta) \frac{P_t G^2 \lambda^2 \sigma(\theta)}{(4\pi)^2 d_r^4} \cdot \frac{1}{k'TB}. \quad (7)$$

Here, d_r^{-4} , $\sigma(\theta)$, $\omega(\theta)$, and $1/(k'TB)$ respectively model path loss, chest projection, physiological coupling, and noise normalization. To avoid over-penalizing farther LoS candidates in short-range indoor multipath, we add a monotonic logarithmic distance correction with a fixed global α :

$$\text{VSSI} = \log \left(\omega(\theta) \frac{P_t G^2 \lambda^2 \sigma(\theta)}{(4\pi)^2 d_r^4} \frac{1}{k'TB} + 1 \right) + \alpha \log \left(\frac{d_r}{d_0} + 1 \right) \quad , \quad (8)$$

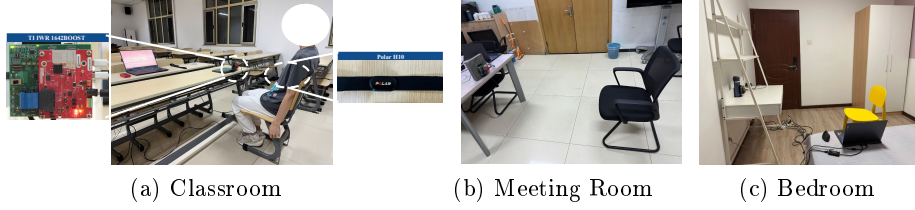


Fig. 8: Experimental scenarios and deployment.

where α scales the distance correction and d_0 is the reference distance (1 m). In deployment, d_r , θ , and LoS can be obtained from robot localization and perception, radar parameters come from device configuration.

6 Evaluation

6.1 Implementation

We evaluate VSSI in HR sensing. As shown in Fig. 8(a), experiments use a TI IWR1642BOOST mmWave radar [6] (77–81 GHz, 2 TX, 4 RX). Raw data is captured via the TI DCA1000EVM [5] and streamed to a PC. Processing is implemented in Python on a laptop (AMD Ryzen 7 5800H, 40 GB RAM), using 10-second windows. Ground-truth HR is obtained from a Polar H10 chest strap [20], synchronized via timestamps.

6.2 Methodology

Experiment setup. As shown in Fig. 8, experiments are conducted in three indoor environments. The subject sits still at distances of 0.5m, 1.5m, and 2.5m, with orientation varied from 0° to 330° in 30° steps (12 angles per distance), yielding 36 configurations. For each, 20–30 segments of 10 seconds are collected, totaling over 27 hours. Experiments follow institutional IRB protocols.

We assume accurate localization, a static subject, and unobstructed LoS, corresponding to an initial deployment stage where the robot has localized a seated target and enumerated LoS candidate viewpoints.

Evaluation Metrics. To assess how well VSSI approximates *a-posteriori* SQ, we quantify ranking consistency across positions using: (i) Spearman rank correlation coefficient; (ii) Absolute ranking error, defined as $|\text{rank}_{\text{VSSI}} - \text{rank}_{\text{SQ}}|$, across 36 distance-angle combinations.

HR estimation error serves as the performance metric for the case study.

Baselines. We compare VSSI with two baselines:

- (i) *Distance-Only* SQ_{dist} : assumes constant RCS σ_1 : $\text{SQ}_{\text{dist}} = \frac{P_t G^2 \lambda^2 \sigma_1}{(4\pi)^2 d_r^4} \cdot \frac{1}{k' T B}$.
- (ii) *Angle-Only* SQ_{angle} : incorporates $\omega(\theta)$ and $\sigma(\theta)$, with distance normalized by d_r^4/d_0^4 ($d_0 = 1\text{m}$): $\text{SQ}_{\text{angle}} = \omega(\theta) \cdot \frac{P_t G^2 \lambda^2 \sigma(\theta)}{(4\pi)^2 d_r^4} \cdot \frac{d_r^4}{d_0^4} \cdot \frac{1}{k' T B}$.

For identical VSSI, ties are broken by prioritizing smaller d_r , then smaller θ .

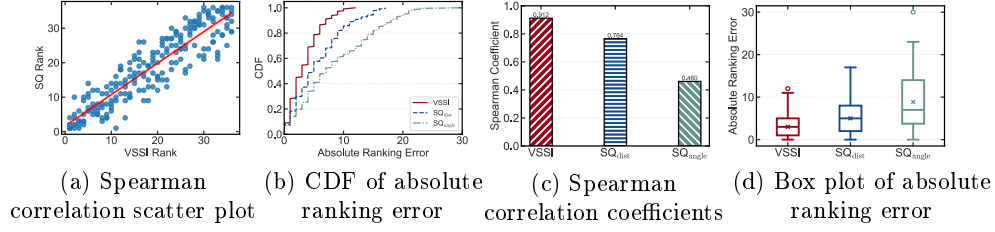


Fig. 9: Overall performance.

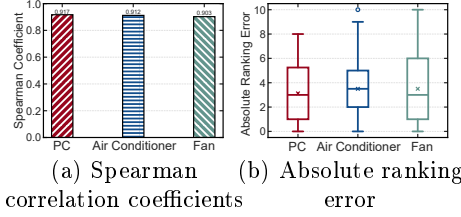


Fig. 10: VSSI-SQ Relationship under Different Interference Conditions.

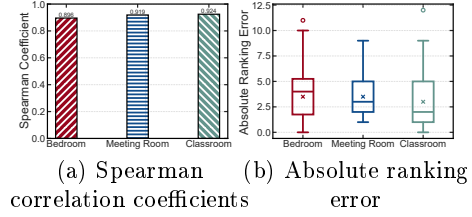


Fig. 11: VSSI-SQ Relationship across Different Environments.

6.3 Overall Performance

We first evaluate the overall performance of VSSI. As shown in Fig. 9(a), VSSI exhibits a clear positive Spearman correlation with SQ, indicating strong monotonic consistency. Fig. 9(b)–(d) further compare VSSI with two baselines in terms of ranking error and correlation. Overall, VSSI achieves higher correlation with SQ and lower ranking error across the evaluated settings.

6.4 Impacting Factors

Impact of Interference Object. We evaluate robustness under close-range vibrational interference from three household devices: a laptop fan with metronome beats, a tower air conditioner, and a pedestal fan. Each device is placed within 5cm of the target at $\theta = 90^\circ$, often touching the arm or chest. As shown in Fig. 10, such interference has minimal effect on VSSI-SQ correlation.

Impact of Different Environments. We test performance across a classroom, meeting room, and bedroom (Fig. 8). As shown in Fig. 11, the Spearman correlation exceeds 0.89, and the mean absolute ranking error remains below 4.

6.5 Case Study

We conduct the HR sensing case study using a simple frequency-domain pipeline (phase extraction, 0.8–2.0 Hz filtering, FFT peak detection), ensuring gains arise from VSSI-guided positioning rather than advanced algorithmic processing.

VSSI is complementary to advanced processing methods (*e.g.*, mmECG [23], mmHRR [11]) by improving the underlying signal quality. As an a-priori guide,

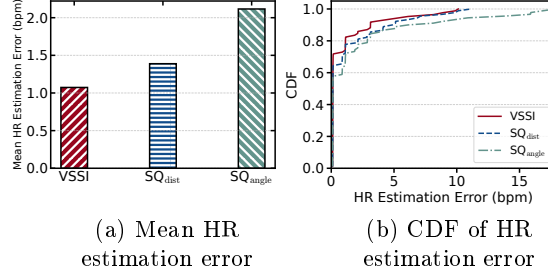


Fig. 12: HR Estimation Performance at Top-Ranked Distance–Angle Configurations.

it selects favorable sensing geometries, enhancing intrinsic signal strength and reducing reliance on back-end processing.

We compare VSSI with two baselines by selecting the top-6 ranked positions from each method. As shown in Fig. 12, VSSI consistently achieves lower HR estimation error, demonstrating its effectiveness for position selection.

7 Conclusion

Despite advances in mmWave vital sign sensing, proactive sensing position selection remains underexplored. This paper introduces VSSI, an a-priori metric that predicts sensing quality from spatial factors before data acquisition. We derive and validate an a-posteriori SQ formulation, and incorporate distance and orientation (via RCS) for accurate prediction. Experiments show that VSSI effectively guides position selection and improves HR estimation performance, marking an important step toward practical, embodied mmWave sensing systems. Future work will study cross-user calibration, motion robustness, and deployment under partial occlusion or localization uncertainty.

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