Request for Proposals

for Solutions to IEEE AESS Challenge Problem I: Radar

July 19, 2025

Abstract

IEEE Aerospace and Electronic Systems Society (AESS) Board of Governors (BoG) funded the development of the first IEEE AESS Challenge Problem in the area of radar. The IEEE AESS Challenge Problem I: Radar is entitled "Radar-Based Heartbeat Monitoring in Dynamic Scenarios." The challenge problems are intended to stimulate excitement and interest about research in the area of radar. This request for proposals (RFP) is for the development of solutions for this challenge problem. As many as four (4) proposals in response to this RFP will be funded to develop solutions for "Radar-Based Heartbeat Monitoring in Dynamic Scenarios."

1. Introduction

The IEEE Aerospace and Electronic Systems Society (AESS) Board of Governors (BoG) is funding the development of challenge problems and solutions in technical areas of AESS. The challenge problems are intended to stimulate excitement about research problems of interest to AESS members. Following the development and publication of a challenge problem, AESS is soliciting proposals for the investigation and development of solutions to the challenge problem. It is anticipated that four (4) proposals for solutions will be funded and those solutions will be presented at an AESS-sponsored conference in a special session. It is anticipated that solutions will have varying levels of complexity and the multiple solutions will lead to confidence in the technical approaches and implementations in real-world applications.

AESS selected radar systems for its first challenge problem as that is of great interest in the AESS community. Additional challenge problems in other areas of interest to AESS members will be released over the next few years. An RFP was issued for the IEEE AESS Challenge Problem I: Radar and the proposal entitled "Radar-Based Heartbeat Monitoring in Dynamic Scenarios" was selected for funding. That challenge problem was proposed and developed by Drs. Yu Rong and Daniel Bliss of Arizona State University and Drs. Kawon Han and Christos Masouros of University College London. The challenge problem is described in Appendix A. This RFP solicits proposals for solutions to IEEE AESS Challenge Problem I: Radar, "Radar-Based Heartbeat Monitoring in Dynamic Scenarios." It anticipated that four (4) proposals for solutions will be funded through this RFP and those solutions will be presented at a future IEEE Radar conference in a special session.

The RFP is organized as follows. Section 2 gives the objective of this RFP, while Section 3 provides the program details and schedule. Section 4 defines the format and requested content for the proposal. Section 5 summarizes the selection criteria and Section 6 provides concluding remarks.

2. Objective

This RFP solicits proposals for solutions to the IEEE AESS Challenge Problem I: Radar, "Radar-Based Heartbeat Monitoring in Dynamic Scenarios." This challenge problem is available publicly and four proposals for solutions will be funded up to $25k each. Those solutions will be presented at an IEEE Radar conference in a special session. It is anticipated that solutions will have varying levels of complexity and the multiple solutions will lead to confidence in the technical approaches and implementations in real-world radar applications.

3. Program and Schedule

Proposals for solutions to "Radar-Based Heartbeat Monitoring in Dynamic Scenarios" as documented in Appendix A are due by September 15, 2025 and should be submitted via e-mail to Dr. W. Dale Blair at dale.blair@gtri.gatech.edu and Professor Sabrina Greco at maria.greco@unipi.it . Proposals should include a cost estimate that shall not exceed $24,500. The challenge problem has been scoped so that one working in the area of the problem can provide a meaningful contribution for less than $25,000. AESS will select four proposed solutions for funding before October 1, 2025 and funding will be made available prior to December 1, 2025. The solution developers will deliver a paper describing their solution by February 15, 2026 so that it can be considered for publication at the 2026 IEEE Radar Conference.

Table 1. Planned Schedule for Solutions to IEEE AESS Challenge Problem I: Radar

Event	Due Date
RFP for Solutions for the Radar Challenge Problem	July 15, 2025
Proposals for Solutions for the Radar Challenge Problem	September 15, 2025
Selection of four Proposed Solutions for Radar Challenge Problem	October 1, 2025
Funding to Four Selected Proposals	December 1, 2025
Papers Describing Solutions for the Radar Challenge Problem	February 15, 2026

4. Format and Content of Proposals

Proposals should not exceed 10 pages in 12 pt font. Biographical information may be included in an appendix and that is not subjected to the limits. Proposals should include the following sections.

Abstract: Abstract for the proposal with less than 250 words.

Introduction: Introduce the reader to your understanding of the challenge problem, summarize the research associated with your solution to the problem, and explain your connection to the area.

Technical Description of Proposed Solution: Provide a technical description of the proposed solutions to the Radar Challenge Problem with justification for your approach and references.

Implementation Plan: Explain your plan for implementation of your solution for the challenge problem.

Milestone Schedule and Developers: Include a milestone schedule that includes progress reports and briefings. Also, provide a list of all proposed deliverables that include a paper for the 2026 IEEE Radar Conference that describes your solution to the problem.

Key Investigators: Provide very brief biographies of key investigators who will be used in this effort.

Cost: Provide a cost estimate for the development of your solution to the challenge problem. Costs may include materials and supplies and employee labor.

References: Provide references to key research in the area of your proposed challenge problem.

5. Evaluation Criteria

Proposals for solutions to the challenge problem will be judged on the

1. Proposers Understanding of the challenge problem 20%
2. Proposed Technical Solution 40%
3. Implementation Plan 20%
4. Subject matter expertise of developers 10%
5. Anticipated impact on real-world radar systems 10%

6. Concluding Remarks

It is anticipated that this RFP will lead to funding for the development of solutions for the radar challenge problem and the presentation of solutions will stimulate excitement in the radar community. The challenge problem is also available to the public for development of solutions by any researchers.

Appendix A

IEEE AESS Challenge Problem I: Radar

“Radar-Based Heartbeat Monitoring in Dynamic Scenarios”

Radar-Based Heartbeat Monitoring in Dynamic Scenarios

Yu Rong[1], Kawon Han[2], Christos Masouros[2], Daniel W. Bliss[1]

***Abstract*—This paper presents a fundamental challenge in radar-based health monitoring: accurately estimating average heart rate and heart rate variability (HRV) in the presence of random body movements (RBMs), as illustrated in Fig. 1. Conventional radar-based heartbeat monitoring systems are highly susceptible to motion artifacts, which limits their effectiveness in real-world scenarios with uncontrolled movements. The proposed challenge aims to develop robust signal processing algorithms that mitigate these artifacts, thereby enabling accurate heart rate and HRV estimation in dynamic environments. This is the first effort to implement open datasets and establish metrics for fair comparisons of motion-robustness in radar-based health monitoring systems, which have yet to be developed. The developed solutions will estimate average heart rate and HRV, with performance evaluated using root mean square error (RMSE) and cross-correlation metrics against reference signals. The success of this challenge will advance biomedical radar signal processing, improving the reliability and robustness of radar-based health monitoring systems. The outcomes will promote broader adoption of wireless sensing in healthcare, smart homes, automotive safety, and beyond.**

***Index Terms*—Biomedical radar, heartbeat rate variability (HRV), random body movement, vital sign radar.**

I. Introduction

Radar-based wireless sensing systems, particularly those applied in biomedical fields, have demonstrated the capability to non-invasively measure a variety of physiological signals, including heartbeat, thorax movements from breathing, and other subtle body motions. The non-contact nature of radar sensing makes it particularly attractive for continuous monitoring in diverse environments. Furthermore, radar sensors offer unique advantages over optical systems due to their all-weather functionality, privacy-preserving characteristics, and the ability to penetrate specific materials.

Aligned with the growing trend in the healthcare industry, where investments in digital healthcare have surged twentyfold over the past decade [1], radar-based health monitoring sensors have garnered significant industrial interest. Notable examples of this trend include products such as Google's Nest Hub [2], Vayyar's in-cabin monitoring [3], and Xandar Kardian's vital signs monitoring radar [4]. These systems are being integrated into smart homes, automotive safety applications, and Internet of Things (IoT) healthcare devices, enabling continuous monitoring of individual well-being without the need for intrusive devices.

This technology has also been extensively studied in the academic field, gaining attention due to its potential for non-invasive health monitoring and widespread applications [5]. The development of radar technology for vital sign detec-

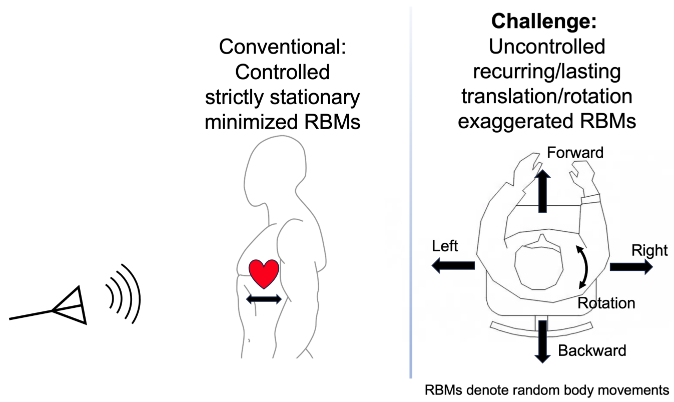

Fig. 1. Cartoon sketch illustrating the challenging scene for radar-based heartbeat monitoring. Left side: the conventional stationary scenario favored by the majority of radar health monitoring studies; right side: the proposed scenario for the challenge problem consisting of the uncontrolled random body movements (RBMs).

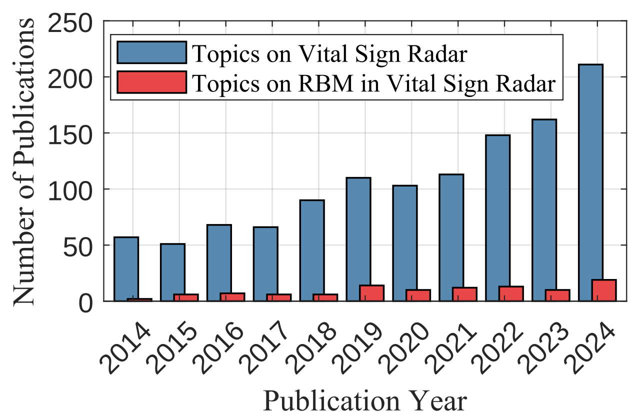

Fig. 2. The number of publications for the topics on vital sign radar and RBM in vital sign radar.

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tion spans a wide range of academic disciplines, from the advancement of radar hardware to sophisticated signal processing techniques for accurate physiological signal monitoring. Since 2014, academic interest in ”vital sign radar” has grown significantly, as illustrated in Fig. 2. However, over 90% of the existing literature focuses on controlled environments with stationary human subjects. In contrast, less than 10% of studies have explored random body movements (RBMs) in vital sign radar with dynamic or real-world scenarios. This paper highlights the lack of robust approaches in such settings as a key challenge in the field.

This research area has presented and addressed several technical questions, making it an intriguing problem for researchers. The miniaturization of radar hardware for real-time, portable, and low-power applications requires continuous innovations in hardware design and RF technologies [6]. From a signal processing perspective, a key challenge is accurately extracting subtle physiological signals, such as heart rate and respiration, from the radar data amidst environmental noise and interference [7]. Ensuring the efficient real-time processing of radar signals while maintaining high accuracy is a critical hurdle in developing radar health monitoring systems.

Although significant efforts have been made over the past decades, the practical application of radar-based vital sign detection remains limited due to its vulnerability to motion artifacts, commonly referred to as RBMs. These artifacts present a significant challenge in real-world applications, where individuals may engage in various everyday activities. While some academic and industrial researchers have addressed this issue, the developed solutions typically perform well only in constrained scenarios or in the presence of small, controlled body movements. Existing approaches to mitigate RBMs often involve complex system designs [8] or auxiliary sensors [9], adding high cost and complexity to the monitoring system. Furthermore, these solutions remain empirical and lack rigorous theoretical underpinnings, often failing to provide consistent performance in uncontrolled, real-world environments. Also, unified performance metrics and figure-of-merit (FoM) for evaluating the effectiveness of these solutions have yet to be established, further complicating progress in this area.

Given these limitations, We propose a challenge focused on developing advanced RBM cancellation techniques to enable motion-robust radar sensing. This challenge problem aims to overcome the existing barriers and extend the application of this emerging technology into a broader range of real-world scenarios, ultimately enhancing the robustness and reliability of radar-based health monitoring systems. These challenges make radar-based health monitoring academically stimulating and a critical field for multidisciplinary collaboration, encompassing biomedical engineering, electrical engineering, and computer science.

The impacts of the proposed challenge problem are highlighted as follows:

- A dataset is specifically collected for the challenge problem of RBM cancellation in radar-based vital sign monitoring. This dataset includes scenarios with unconstrained movements, enabling the research community to benchmark algorithms and compare performance across different approaches. The availability of the dataset will help drive innovation, facilitate reproducibility, and encourage a more significant effort to solve the motion artifact challenge.
- Establishing performance metrics and figure-of-merit (FoM) for evaluating radar-based heart activity monitoring systems will provide a standardized framework for assessing different approaches to motion artifact cancellation. This will promote more consistent and meaningful comparisons across academic and industrial research, accelerating progress in the field.
- The challenge problem drives innovations and advancements in radar signal processing algorithms, particularly in separating physiological signals from motion artifacts, which remains unsolved.
- The success of this challenge will lead to broader adoption of radar technology in healthcare and beyond, reducing system complexity and cost by eliminating the need for auxiliary sensors or complex system designs. This will make radar systems more accessible for various applications, leading to more widespread and practical implementations in industries such as remote health monitoring, automotive safety, and consumer wellness products.

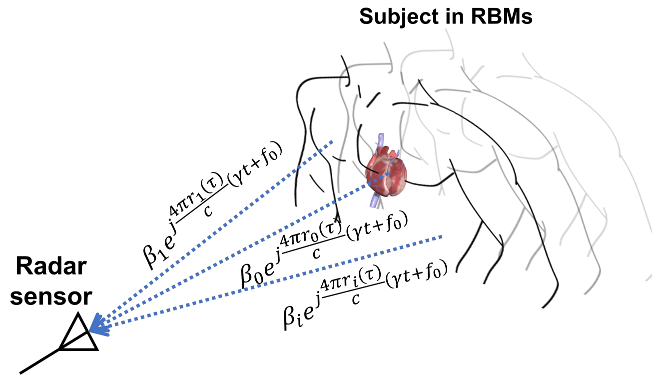

Fig. 3. Modeling of dynamic human scattering field including vital motion and RBMs.

II. Problem Statement

This challenge problem focuses on the robust estimation of human heart rate and its variability in the presence of RBMs using a single radar system without auxiliary sensors. Uncontrolled deep respiration and body movements introduce significant noises and artifacts into the radar signal, making this task particularly challenging. These strong RBMs exhibit wideband characteristics that overlap with the frequency range of heartbeat signals, complicating the isolation and extraction of accurate cardiac information.

We frame this problem using a frequency-modulated continuous wave (FMCW) radar, a widely utilized technology in industrial applications [10]. The transmitted FMCW chirp signal is analytically described by

$$y_{\mathrm{TX}}(t,\tau) = \exp\left(j \cdot \left(2\pi f_0 t + \pi\gamma t^2\right)\right), \tag{1}$$

where $\gamma = B/T_c$ is the frequency ramp slope, f_0 is the start frequency, t represents the fast time ranging from 0 to T_c, and τ is the slow time.

When this signal is reflected off a human subject, the received signal at time τ can be expressed as

$$y_{\mathrm{RX}}(t,\tau) = \sum_{i=0}^{N-1} \beta_i(\tau) \cdot s_{\mathrm{TX}}\left(t - \frac{2r_i(\tau)}{c}\right) + w(t,\tau), \tag{2}$$

where $r_i(\tau)$ represents the distance from the radar to the i-th body part, $\beta_i(\tau)$ is the complex amplitude representing reflection strength, and N is the number of body parts contributing to the reflections in Figure 3. The noise $w(t,\tau)$ is modeled as additive white Gaussian noise (AWGN), following $\mathcal{CN}(0,\sigma^2)$. The received signal is then mixed with the transmitted signal, producing the beat signal

$$y_b(t,\tau) = \sum_{i=0}^{N-1} \beta_i(\tau) \exp\left(j\frac{4\pi r_i(\tau)}{c}(\gamma t + f_0)\right) + w_b(t,\tau). \tag{3}$$

Let $r_0(\tau)$ denote the distance corresponding to the body part related to heartbeat activity, described as

$$r_0(\tau) = h(\tau) + u(\tau) + d_0, \tag{4}$$

where $h(\tau)$ represents the displacement caused by heartbeat activity, $u(\tau)$ represents unwanted motion artifacts (e.g., breathing), and d_0 is the initial distance between the radar and the target. Then, the beat signal can be rewritten as:

$$\begin{aligned} y_b(t,\tau) = \beta_0(\tau) \exp\left(j\frac{4\pi(u(\tau)+d_0)}{c}(\gamma t + f_0)\right) \\ \exp\left(j\frac{4\pi h(\tau)}{c}(\gamma t + f_0)\right) \\ + \sum_{i=1}^{N-1} \beta_i(\tau) \exp\left(j\frac{4\pi r_i(\tau)}{c}(\gamma t + f_0)\right) + w_b(t,\tau). \end{aligned}$$

In this formulation, the desired signal component is $h(\tau)$, which exhibits periodic patterns that can be analyzed to estimate both the heartbeat rate and HRV. All other terms, whether additive or multiplicative, are treated as motion interference, complicating the extraction of $h(\tau)$ from $y_b(t,\tau)$. The heartbeat-related displacement $h(\tau)$ may not be limited to chest motion [11]; it could also include other heartbeat-induced vibrations, such as heart sounds [12]. Therefore, the extraction of the periodic heart activity features $s(\tau)$ can be derived directly from $h(\tau)$ or may be achieved through any novel approach developed by the problem solver.

It is important to note that the motion patterns of $u(\tau)$ and $r_1(\tau), r_2(\tau), \ldots, r_{N-1}(\tau)$ are considered random and cannot be explicitly modeled, as the challenge problem is designed to address uncontrolled body motion scenarios. Consequently, the target may not remain within the same range bins throughout the measurement, leading to potential range migrations over time [13]. These range shifts further complicate signal processing and require robust techniques to handle. The exact methods for processing the received signals and addressing these challenges are left to the solvers of this problem and will not be specified at this stage.

To further clarify the challenge problem, the problem solvers are required to design signal processing algorithms while adhering to the following constraints:

- **(C.1)** Radar system parameters such as operating frequency, bandwidth, chirp configuration, and sampling rate are pre-specified. However, hardware imperfections, such as I/Q imbalance, may still affect the signal.
- **(C.2)** No prior information about the target is available. This includes factors like the target's distance from the radar, heartbeat templates in normal conditions, or RBM patterns.
- **(C.3)** There are no restrictions on how the heartbeat rate and HRV are estimated, but the coherent processing interval (CPI) of the sliding window for estimating the heartbeat rate must be equal or less than 10 seconds. Solvers are free to exploit either the displacement information $h(\tau)$ or amplitude variations $\beta_0(\tau)$, among other approaches.

Finally, the specific objectives for this challenge are summarized as follows:

- **(P.1)** Estimate the average heartbeat rate f_h over a given coherent processing interval from the radar-based measurement $y_b(t,\tau)$.
- **(P.2)** Estimate the heartbeat rate variability $\Delta_h(\tau)$ (i.e., RR intervals) by extracting time-domain heart motions $s(\tau)$ from the radar-based measurement $y_b(t,\tau)$.

Although these two objectives may appear similar, they represent distinct difficulty levels. **(P.1)** involves calculating the average heartbeat rate, which can be done using frequency-domain analysis and is generally less challenging. This is because it does not require exact recovery of the time-domain features of heart activity—integrating the signal allows for an estimation of the average heart rate [14]. On the other hand, **(P.2)** is more challenging, as it requires tracking the precise peak-to-peak time intervals between consecutive heartbeats without relying on signal averaging [15]. This necessitates accurate time-domain feature extraction and presents a higher level of complexity.

It should be noted that average heart rate (**P.1**) and heart rate variability (**P.2**) are used in different application areas. For example, average heart rate is often sufficient for fitness and general health monitoring, while HRV provides deeper insights into autonomic nervous system function and is more critical in medical diagnostics, stress detection, and performance monitoring.

III. Performance Metrics

A. Metric for Average Heart Rate

For the evaluation of the average heart rate estimation, we use the root mean square error (RMSE) to assess the difference between the estimated heart rate $\hat{f}_h$ and the true heart rate $f_{h,0}$, as provided by the reference contact-based sensor. The CPI for averaging can be determined by the solution developer within the range of $T_{CPI} \leq 10s$. Each dataset is measured over a total time duration T_M. The average heart rate must be estimated and evaluated within the time range of $[T_{\text{CPI}}/2, T_M - T_{\text{CPI}}/2]$, using a sliding step of 1 second. Let $\hat{\delta}_{\text{AHR}}$ represent the RMSE of the estimated average heart rate, which is computed as

$$\hat{\delta}_{\text{AHR}} = \sqrt{\frac{1}{T_M - T_{\text{CPI}} + 1} \sum_{n=T_{\text{CPI}}/2}^{T_M - T_{\text{CPI}}/2} \left(f_{h,0}(n) - \hat{f}_h(n) \right)^2}. \tag{5}$$

However, this metric may be skewed if a large coherent processing interval is chosen. The following points explain why this could lead to an unfair performance assessment: (1) it is well-known that the accuracy of frequency estimation improves with a more significant number of samples, (2) estimating the average heart rate over a shorter time interval is a more desirable solution to be employed in the real-time, and (3) the evaluation of dynamic RBM cancellation performance could be distorted. To address this, we modify the RMSE metric by incorporating the CPI length, providing a more balanced figure-of-merit (FoM):

$$\text{FoM}_{\text{AHR}} = \frac{1}{T_{\text{CPI}} \cdot \hat{\delta}_{\text{AHR}}}. \tag{6}$$

B. Metric for Heart Rate Variability

RMSE is used as the primary performance metric to evaluate the performance of HRV estimation in this challenge. The RMSE calculates the difference between the estimated RR intervals, $\hat{\Delta}_h$, and the true RR intervals, $\Delta_{h,0}$, over the entire measurement period T_M. Unlike average heart rate estimation, the CPI is not required for HRV evaluation, as HRV is measured in the time domain based on each detected heartbeat peak. Given a total of $\hat{M}$ RR intervals during the measurement period, the RMSE is calculated as follows:

$$\hat{\delta}_{\text{HRV}} = \sqrt{\frac{1}{\hat{M}} \sum_{n=1}^{\hat{M}} \left(\Delta_{h,0}(n) - \hat{\Delta}_h(n) \right)^2}. \tag{7}$$

However, this RMSE metric does not fully capture discrepancies in the number of detected RR intervals compared to the reference. We introduce an additional performance metric based on the cross-correlation between the estimated time-domain heart motion signal $s(\tau)$ and the reference signal $s_r(\tau)$ to account for these mismatches. The cross-correlation is computed as

$$\text{C}_h = \frac{\sum_{\tau=0}^{T_M} s(\tau) s_r(\tau)}{\sqrt{\sum_{\tau=0}^{T_M} (s(\tau))^2 \cdot \sum_{\tau=0}^{T_M} (s_r(\tau))^2}}. \tag{8}$$

Finally, by combining both the RMSE and cross-correlation measures, we define the FoM for HRV estimation as

$$\text{FoM}_{\text{HRV}} = \frac{\text{C}_h}{\hat{\delta}_{\text{HRV}}}. \tag{9}$$

C. Scoring Plan

The overall score for the challenge is computed as a weighted sum of the normalized figures of merit, FoM_{AHR}, FoM_{HRV}, and the computational complexity. To ensure consistency, FoM_{AHR} is normalized to a value of 100 when the RMSE of the average heart rate estimation is 1 bpm and the CPI is 10 seconds. Similarly, FoM_{HRV} is normalized to 100 when the HRV estimation RMSE is 16.7 ms (equivalent to a 1 bpm error in heart rate) and the cross-correlation value is 0.9. The overall score formula is given by

$$\text{Score} = (100 \times 10) \cdot \text{FoM}_{\text{AHR}} + \left(\frac{100}{60 \times 0.9} \right) \cdot \text{FoM}_{\text{HRV}}. \tag{10}$$

This formula balances the accuracy of both the average heart rate and HRV estimates, ensuring that each contributes proportionally. Finally, with D datasets in total, the average score of all datasets is the final score as

$$\text{Score}_{\text{Total}} = \frac{1}{D} \sum_{i=1}^{D} \text{Score}\left[\text{dataset } i\right]. \tag{11}$$

An evaluation tool with detailed instructions will be provided for the challenge participants.

IV. Challenge Demonstration

A. RBM effects

Radar remote heartbeat data analysis is presented in two challenging settings: deep breathing and back-and-forth movements, as one example of RBMs. The stationary case is used as the ideal baseline in the comparison study. Deep breathing can lead to elevated body movements and make it difficult to detect the fundamental heartbeat. RBMs not only generate large-scale body movements but also signal leakage among range bins or range migration.

Effects of these man-made body movements on a 77 GHz radar signal return are pictorially presented in Fig. 4. Stationary human pattern focuses at 0.4 meters in the range profile (a.1). Deep breathing appears as a few disconnected patterns within the same range (b.1). However, the RBMs manifest a back-and-forth wander around 0.4 meters (c.1). The raw Fourier spectra of the complex signal at 0.4 meters show an increase in spectral content and patterns from (a.2) to (c.2). The DC component has been suppressed by mean subtraction. The RBMs behave as a wideband signal with a significant spectral energy around 20 Hz. The motion index is a measure of movement activity in the scene. It is calculated as the

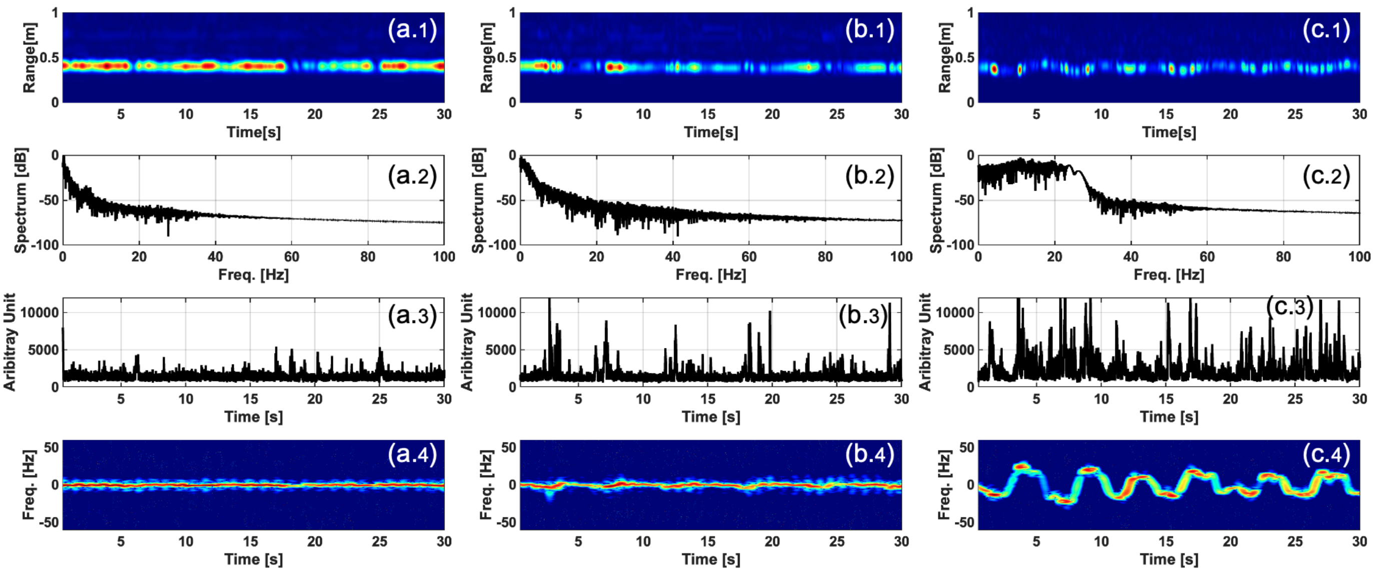

Fig. 4. Motion effects on radar signals. (a), (b) and (c) represent three scenarios: stationary, deep breathing, and RBMs. In RBMs, the subject performs back-and-forth movements continuously during the experiment. (1)-(4) represent 4 different data visualizations in the form range profile (1), raw signal spectrum (2), motion index (3), and micro-Doppler signatures (4).

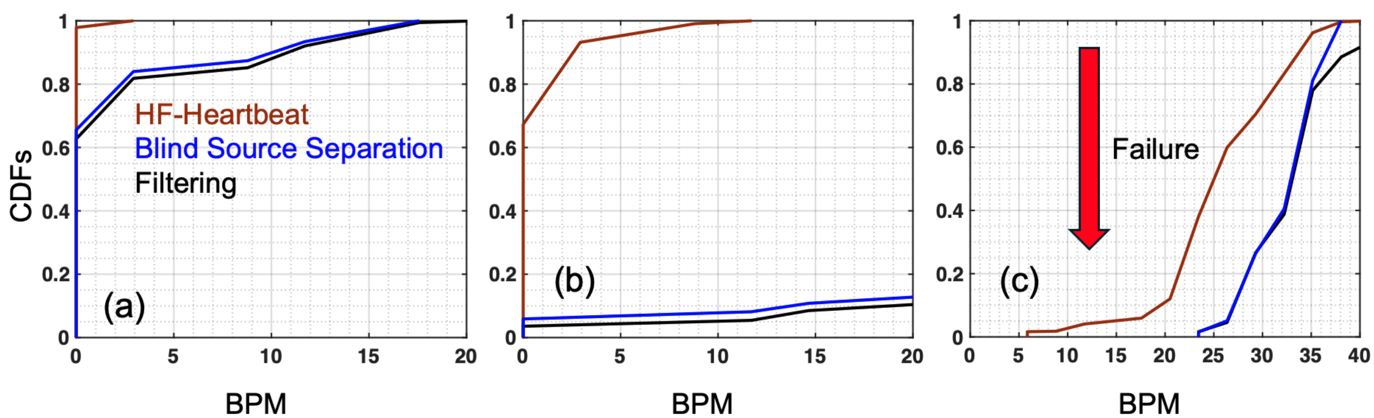

Fig. 5. HR accuracy from three selected algorithms: commonly used spectral filtering and peak-finding approach, variational mode decomposition or its variants based on blind source separation approach, and recently proposed high frequency heartbeat signatures (Seismocardiography and heart sound) based approach. Their HR performance is compared and evaluated in the three scenarios: stationary (a), deep breathing (b), and RBMs (c).

maximum energy dislocation over time. The frequency and intensity of the motion index are gradually increasing from the stationary case (a.3) to deep breathing (b.3), and to RBMs (c.3). Lastly, classic micro-Doppler analysis is presented in (a.4) to (c.4). The short-time Fourier transform is computed using a 1-second time window. The micro-Doppler signatures capture the motion dynamics in each scenario. The Doppler energy focuses on zero frequency in the stationary case (a.4). The increased Doppler energy around zero frequency corresponds to the deep breathing events. The distinct micro-Doppler signature corresponds to the back-and-forth body movements in the RBM scenario (c.4).

B. Comparison of Selective Algorithms

There are some heuristic signal approaches and system-level approaches developed to address the RBM issue in radar-based vital signs. The scope of this proposed challenge focuses on robust practical signal processing methods using only a single mmWave sensor, without auxiliary sensors such as a secondary radar sensor or a visual sensor. Three representative algorithms are evaluated and compared using the datasets from Section IV-A. They have been used in developing other complicated algorithms. The filtering approach refers to the most commonly used method. It designs a notch filter based on the person's normal resting HR. However, it fails to consider individuals with a low resting HR or those with an elevated HR. A blind source separation approach, such as variational

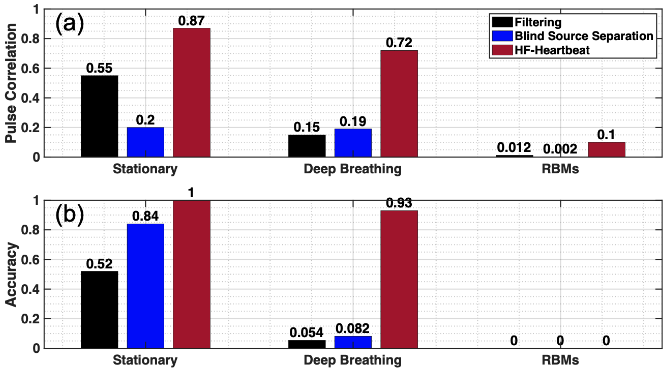

Fig. 6. Correlation and HR accuracy comparison. The estimation performance of the three algorithms is tabulated.

	HF-Heartbeat		Blind Source Separation		Filtering	
	$\mathrm{FoM}_{\mathrm{AHR}}$	$\mathrm{FoM}_{\mathrm{HRV}}$	$\mathrm{FoM}_{\mathrm{AHR}}$	$\mathrm{FoM}_{\mathrm{HRV}}$	$\mathrm{FoM}_{\mathrm{AHR}}$	$\mathrm{FoM}_{\mathrm{HRV}}$
Stationary	255.4	106.6	13.2	1.8	13.2	4.0
	Score: 362.1		Score: 15.0		Score: 17.2	
Deep breathing	115.7	12.5	3.7	1.1	3.5	0.8
	Score: 128.1		Score: 4.8		Score: 4.3	
RBMs	3.4	0.4	3.0	0.0	2.6	0.0
	Score: 3.8		Score: 3.0		Score: 2.6	
Total score	**164.7**		**7.6**		**8.0**	

Fig. 7. Summary of scores evaluated by FoMs of the challenge problem.

mode decomposition and its variants, has been used to isolate a weak pulse signal from other motion artifacts. However, it suffers from this low signal-to-noise ratio problem, and the performance is not guaranteed. Recently, a new method using high-frequency (HF) heartbeats to derive the fundamental heartbeat has been proposed and demonstrated, yielding some encouraging results. HF refers to cardiac phenomena observed in Seismocardiography and Phonocardiography. However, this approach did not account for RBM cancellation and can be improved with an active RBM cancellation technique.

The cumulative density functions (CDFs) of the HR accuracy are plotted in Fig. 5. The HR accuracy is calculated with a 10-s sliding window with a step size of 50 milliseconds. As the level of motion effects increases, the CDFs degrade and eventually completely fail in the RBMs (c). In the stationary case, the HF-heart approach almost achieves perfect performance, followed by blind source separation and filtering methods (a). In the deep breathing case, the HF-heartbeat approach maintains good performance while the others deteriorate significantly.

In particular, statistics of pulse correlation and accuracy at a tolerance of 3 bpm are summarized in Fig. 6.

C. Score of Algorithms

Each selected algorithm is evaluated based on its performance in estimating average HR and HRV. Using the FoMs defined in (6) and (9), the score for each dataset is calculated according to (10), and the overall average score across all datasets is computed as shown in (11). A summary of the final scores for the selected algorithms is presented in Fig. 7. The results show a strong alignment with the performance analysis discussed in Section IV-B, where the HF-heartbeat approach demonstrates superior performance compared to the others. However, it is also evident that all algorithms perform poorly under RBMs, resulting in significantly lower scores for RBM datasets. This highlights the critical need for more advanced solutions that can mitigate RBM effects, particularly in dynamic and real-world scenarios, thereby motivating further development efforts.

V. Suggestions for Potential Solvers

We highlight a critical challenge in radar-based heartbeat recovery and estimation, demonstrating how RBM affects radar signals at various stages and leads to inconsistent HR accuracy when using standard methods. These sensing failures underscore the need for novel signal processing techniques and a fundamental redesign of the existing radar vital sign processing chain.

We encourage researchers to develop robust and practical solutions. While a scoring system is implemented to evaluate proposed approaches, participants are strongly advised to provide sufficient justifications for their methods. Potential solutions are not limited to classical signal processing but also include bio-inspired machine learning, deep learning, and transfer learning techniques that leverage pretrained models and datasets. Contributions from all proposers will be vital to advancing radar-based vital sign sensing, enabling reliable performance in real-world, free-living environments.

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