Target-Oriented WiFi Sensing for Respiratory Healthcare: from Indiscriminate Perception to In-Area Sensing

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***Abstract*—Driven by the vision of integrated sensing and communication (ISAC) toward 6G technology, the WiFi-based respiration sensing approach has emerged as a highly competitive candidate for advanced healthcare services. Nevertheless, the indiscriminate perception of all the moving objects within the sensing area raises challenges for system stability and robustness for real-world deployment, especially for the susceptibility to motion interference from other people. Meanwhile, thanks to the emerging in-area wireless sensing technologies, *i.e.*, beamforming, the dynamic environment tolerance of these technologies gives crucial opportunities for target-oriented WiFi-based healthcare services. This article discusses the compelling intersection of in-area WiFi sensing and the future of target-oriented intelligent respiratory healthcare network services. We first present a novel WiFi-based healthcare-assisting framework tailored for inter-user motion interference-tolerable (IMIT) sensing. The detailed components of low-level signal preprocessing, target-direction signal extraction, and healthcare-related services are discussed. By utilizing CSI beamforming technology, which adjusts a directional beam toward the desired direction and adaptively places beam nulls in noisy directions, we can mitigate motion interference and achieve target-oriented healthcare sensing. Finally, we discuss open challenges and potential solutions for target-oriented WiFi healthcare sensing.**

I. Introduction

To provide highly integrated and widespread applications for six-generation (6G) integrated sensing and communication (ISAC), the radio frequency (RF)-based solutions have been envisioned as a compelling approach for advanced ubiquitous healthcare services, where people are no longer bound by the attached sensors [1]. Basically, RF-based approaches utilize ambient radio signals, *e.g.*, Frequency-modulated continuous wave (FMCW), mmWave, radio-frequency identification (RFID), and WiFi, to capture human movements and interpret them into health status data. Among all of them, the WiFi-based solution has become a competitive candidate since it is ultra-dense deployed, low cost, privacy preservation, and less susceptible to line-of-sight (LoS) occlusions compared with other short-wavelength RF-based solutions [2].

While showing promising progress, existing WiFi-based healthcare systems are still not yet suitable for practical deployment [3]. One of the main reasons is their indiscriminate perception of all the concurrent non-target moving objects within the sensing area. In such cases, the WiFi channel state information (CSI) tends to capture all motion information within the sensing area, which inevitably leads to potential indistinctness [4], [5]. Traditional WiFi-based systems assume a stationary environment to avoid motion interference from other interferes. However, such a strong assumption may not be reasonable, given that dynamic motion interference is pervasive in practical environments.

Recently, thanks to the emerging in-area wireless sensing technologies [6]–[9], which empower WiFi sensing systems the ability to resist motion interference from non-target individuals, the WiFi-based healthcare system has the potential to achieve a new level of target-oriented sensing. The key to target-oriented sensing is to enhance the sensing capacity to focus on the intended target from the area of interest by isolating and capturing target-specific signals in motion interference-prone environments. For instance, by quantifying the physical separability of motion signals from multiple moving objects [7], [8], or expanding the bandwidth of WiFi signals [9], the motion interference from non-target areas can be mitigated. However, these methods either require a small distance between the target and the WiFi sensor or a sufficient distance between the non-target individuals and WiFi sensors, which may not be applicable to real-world scenarios. There also has been a growing interest in leveraging compressed beamforming reports (CBR) for WiFi sensing [10]. Nevertheless, considering that CBR provides only partial and compressed channel information, the coarse-grain data may pose challenges in accurately extracting target signals within complex and dynamic environments.

To loosen the restrictions of stationary environments and tolerate non-target individuals from carrying out their activities, we propose an inter-user motion interference tolerable (IMIT) framework that integrates beamforming technologies into WiFi sensing systems. Through the adjustment of array weights to control signal directionality, the beamforming approach

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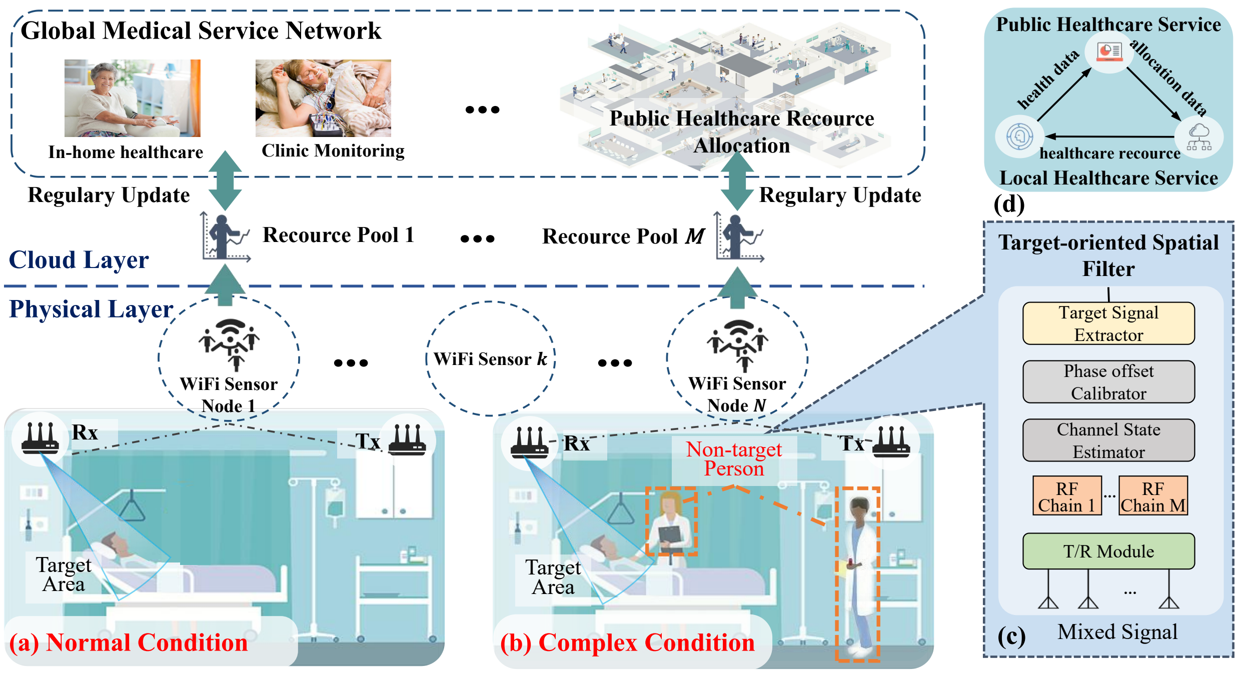


Fig. 1: The hierarchical architecture of target-oriented WiFi healthcare service. Parts (a) and (b) show the normal sensing scenario and complex scenarios with inter-user motion interference, respectively. Part (c) depicts the steps involved in mitigating motion interference, while part (d) illustrates the communication between public healthcare services and local healthcare services.

enables the development of a target-oriented wireless sensing system. In this sense, the paradigm of the WiFi healthcare system shifts from indiscriminate sensing toward target-oriented directional sensing, which can efficiently mitigate motion interference and reconstruct the motion signal of the target user to complete a respiratory health-assisting task.

II. IMIT Architecture for Target-oriented Healthcare Services

As depicted in Fig. 1, the hierarchical IMIT architecture comprises a global medical service network, N local WiFi sensor nodes, and M resource pools. More specifically:

Global Medical Service Network: The global medical service network serves as the backbone of our framework, which provides centralized management and allocation of public healthcare services on a global scale. Similar to the large-scale network [11] described in existing literature, the global medical service network contains comprehensive healthcare data spanning entire regions or even wider areas. Both static data, *e.g.*, patient records and medical facility information, and dynamic data, *e.g.*, real-time patient vital signs, are collected and managed by the network. Moreover, instead of communicating with users directly, the network is periodically updated with data from local WiFi sensor nodes distributed across various healthcare facilities and communities.

Local WiFi Sensor Nodes: In our framework, each healthcare facility or community is equipped with local WiFi sensor nodes that are responsible for local healthcare data collection and target-specific signal extraction. The extracted target signal, along with the patient's identification, is continuously updated to the resource pools. These nodes operate on existing communication infrastructures and maintain close proximity to end-users. By leveraging target-oriented spatial filtering techniques, these nodes can effectively extract target health-related signals even in the presence of non-target individuals. Moreover, the hierarchical structure of the framework enables direct communication between recourse pools and local WiFi sensor nodes, minimizing latency and optimizing data transmission efficiency.

Resource Pools: The virtual resource pools consist of physical entities equipped with sufficient computing and storage resources, *e.g.*, WiFi sensing controller servers acting as edge servers. It performs an initial evaluation of user health status by analyzing the extracted target sensing data from local WiFi nodes, and subsequently transmits the evaluation results, along with user information, to the global network for in-depth analysis. Furthermore, by consolidating resources at the edge of the network, it optimizes physical sensing resource allocation and enhances scalability, ensuring seamless delivery of WiFi sensing services to end-users.

In the WiFi-based IMIT architecture, the global medical service network collects massive amounts of patient health information and deploys them on global databases, which serve as a valuable reference for the allocation of public health resources. Therefore, it has potential applications in areas such as respiratory infectious disease surveillance and prevention, cross-institutional medical collaboration, and remote health monitoring, where massive patient health data in a wide region is required. Moreover, in the event of an urgent health issue, *e.g.*, respiratory arrest, the system provides timely alerts to get medical support. Note that the environments for WiFi sensors are more likely to have more than one person present at the same time in the real world. Thus, the target-oriented spatial filter plays a crucial role in our framework.

III. Conception, Scenarios, and Challenges

To enable IMIT architecture, it is imperative to ensure the robustness of local WiFi sensor nodes against motion interference in complex environments. Let us start by introducing the concept of motion interference and then elaborate on its typical scenarios.

A. Why does Ambient Motion Interference Matter?

Basically, the concept of motion interference in wireless sensing could refer to the disturbance caused by the movement of non-target individuals or objects within the WiFi sensing area when performing wireless sensing tasks. When these movements occur, the interfering signals induced by non-target individuals superimpose with the intended target signals and may distort or even overlap with the desired target signal.

Furthermore, despite the similarities with existing radar systems, the challenges are much greater for WiFi systems due to the inherent differences between these two types of systems. Firstly, different from the superior spatial-temporal resolution of radar systems, the limited bandwidth of WiFi channels (*e.g.*, 20/40 MHz in 802.11n protocol) makes it challenging to distinguish the target individual-induced paths from other noisy paths in the environments [9]. Moreover, WiFi sensing systems often operate in rich-reflective indoor environments, where the presence of motion interference from multiple obstacles and reflectors is inevitable. Therefore, the development of motion interference mitigating techniques is essential and valuable.

B. Typical Motion Interference Scenarios

In line with the most recent scientific works, we try to cope with four typical motion interference scenarios based on the source of motion noise, as illustrated in Fig. 2.

Inter-user Motion Interference: This occurs when multiple subjects are present within the same sensing area, where the signals induced by the irrelevant motion of non-target individuals interfere with the desired target motion signal. Due to the uncertain locations of the non-target interferers, it is important to adaptively filter out the motion noise components from the received signal.

Self-motion Interference: While conducting health monitoring, the irrelevant movements of the targets themselves could potentially obscure the desired motion data. During the sensing process, the received signal contains not only information on target motion but also irrelevant self-motion interference (*e.g.*, the action of leaning or moving limbs). These self-motion actions may cause a sudden fluctuation and lead to an overestimation of the respiration rate.

Device Motion Interference: Device motion factors in the environment, such as the vibrations of devices, can introduce motion noises that contaminate the desired signals. For instance, when we place a WiFi sensor on a moving robot or hold it in hand, the movements of a WiFi device can significantly affect the accuracy of the sensing system [12].

Hybrid Motion Interference: Hybrid motion interference occurs when multiple types of interference occur simultaneously. For example, when we monitor a driver in a moving car, the received signals are the superimposition of both the device's motion interference and the self-motion interference.

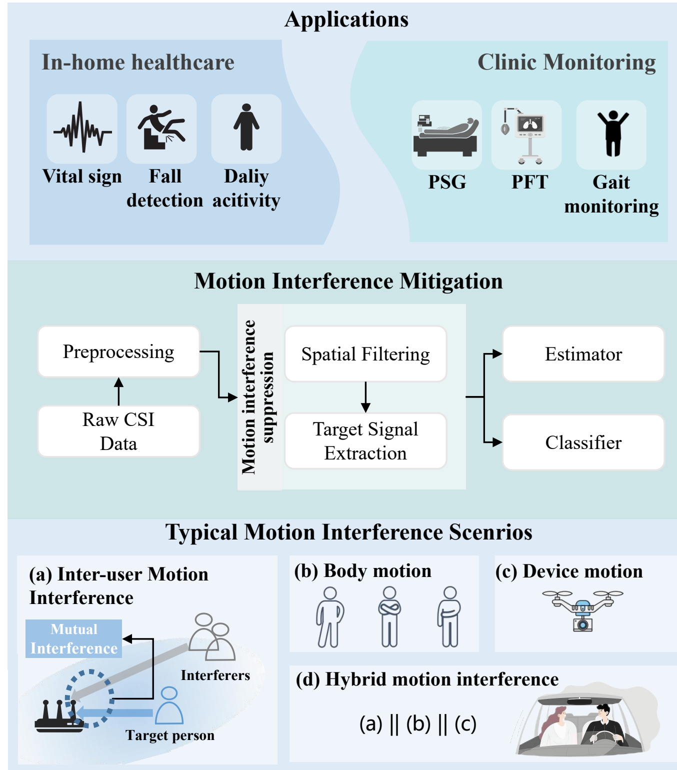


Fig. 2: The hierarchical design for target-oriented WiFi sensing.

In this article, we mainly focus on inter-user motion interference to grant non-target individuals the freedom to carry out their activities and realize target-oriented WiFi sensing.

C. Does Conventional Beamforming work for it?

When it comes to the inter-user motion interference issue in wireless sensing systems, a reliable and direct approach is beamforming, which is also known as spatial filtering. The basic idea of beamforming is to strengthen the signal from a specific direction while suppressing the signals from other directions. However, due to the inherited difference (*e.g.*, spatial-separated transceivers) between WiFi and radar sensing systems, it may not be feasible to apply beamforming technology directly to WiFi sensing systems. Therefore, we ask the question: *does conventional beamforming be applied to commodity WiFi sensing systems to address the inter-user motion interference issue?*

Drawing upon the signal processing method detailed in [13], we explore the feasibility of CSI beamforming and identify the challenges when implementing CSI beamforming on commodity WiFi devices as follows:

- **Time-varying Phase Offsets.** The raw CSI data collected by commodity WiFi receiver contains time-varying phase offsets, *i.e.*, packet detection delay (PDD), sampling frequency offset (SFO), central frequency offset (CFO), etc [14]. Unfortunately, since beam generation requires precise synchronization across the time domain, the presence of those offsets can disrupt the constructive interference needed for beamforming.

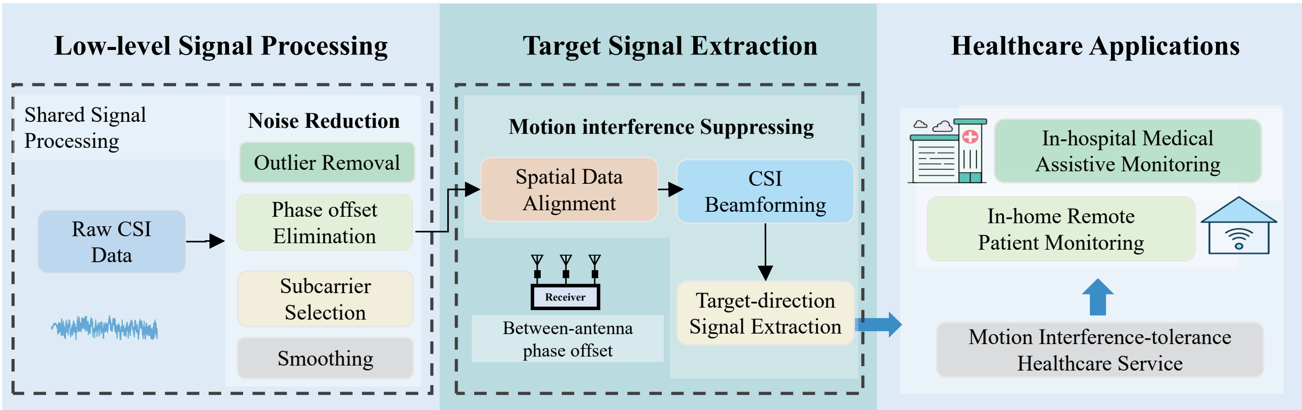


Fig. 3: The system pipeline of target-oriented healthcare monitoring.

- **Deviations to Main Lobe Direction.** Besides the time-varying phase offset, there is still a random time-invariant π phase offset between receiver antennas, which is mainly caused by the phase lock loop (PLL). This lack of alignment of between-antenna phase data results in large deviations of main lobe direction and reduced interference suppression capabilities. Interestingly, as illustrated in Fig. 4, the π-shift phase offsets remain constant after each reboot of the WiFi receiver [15].
- **Side-lobe Interference.** Beamforming algorithms rely on a sufficient number of antennas to generate a narrow and focused beam. With a limited number of antennas, the energy of side lobes is relatively high and is non-negligible. When the interferers appear in side lobe directions, the weak respiration signal may be buried in strong motion interference signals, leading to performance degradation.

IV. Enabling Technologies

To loosen the restrictions of stationary environments and tolerate non-target individuals from carrying out their activities, we propose to add a target-oriented spatial filtering module before the estimation of health-related information. The system is mainly composed of three modules: low-level data prepossessing, target signal extraction, and healthcare-related services. The system pipeline is shown in Fig. 3.

Stage 1: Low-level Signal Preprocessing: Generally, the data preprocessing process involves four steps: outlier removal, time-varying phase offset elimination, subcarrier selection, and smoothing. First, we remove the outliers and then eliminate the time-varying phase offset by adding a constructed reference

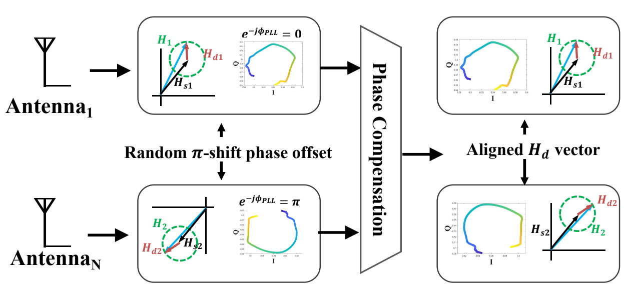


Fig. 4: illustration of between-antenna π-shift phase offset.

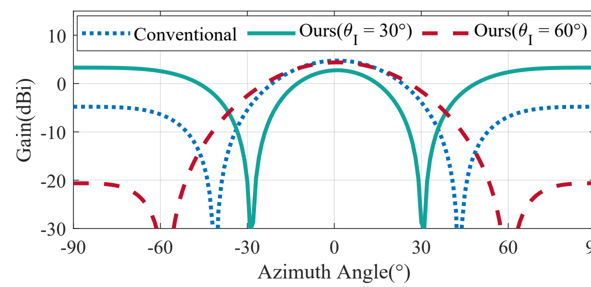


Fig. 5: Comparison of beam patterns between conventional beamforming and DN-BF.

channel [14]. To construct the reference CSI, we calculate the FFT of the combined CSI phase over a time window of 20 seconds and further calculate the energy of human motion by the energy sum of FFT bins in the range of 0.1-20 Hz[1]. The optimal weight $\boldsymbol{W}^*$ is obtained by minimizing the human motion energy. Once the optimal weight $\boldsymbol{W}^*$ is obtained, we constructed the reference CSI based on $\boldsymbol{h}_{ref} = \boldsymbol{W}^{*H}\boldsymbol{X}$, and divided it to each antenna to eliminate the time-varying phase offsets. We then select the most sensitive subcarrier that contains the most respiration energy (*i.e.*, the energy within the respiration frequency range). Afterward, we utilize the Savitzky-Golay filter to filter out the high-frequency noise.

Stage 2: Target-direction Signal Extraction: According to the previous section, the between-antenna phase shift can also induce a large deviation in the beam direction. Thus, before performing DN-BF to mitigate the motion interference of other interferers, we propose a beam direction corrector (BDC) algorithm to compensate for the between-antenna phase shift. The initial PLL phase offsets of a certain antenna element are two possible constant values (*i.e.*, π and 0):

$$|\beta_i - \beta_j| = \pi, \tag{1}$$

where β_i and β_j represent the initial phase of the i_{th} and j_{th} antenna at the same receiver, respectively. Once the PLL phase offset values are determined, they are long-term valid until the WiFi devices are restarted. Assume that the input of the algorithm is the time-varying phase offset calibrated CSI sequence, which is denoted as $H = (\hat{h}_1, \hat{h}_2, \cdots, \hat{h}_M)$.

[1]The normal range for human respiration rate is 0.1-0.5 Hz, while human activity frequencies range from 0-20 Hz.

The strategy of phase compensation is based on the following insight. When the phase offset in each RF chain is correctly compensated, the CSI values between the 2^{nd} to M^{th} antenna and the 1^{st} antenna exhibit the highest similarity.

Afterward, to address the side-lobe interference issue, we design a Directional Nulling BeamForming (DN-BF) scheme that can adaptively suppress the motion interference via the null scan scheme. During the beam null scan process, the CSI array sequentially directs the beam null towards different directions while constraining the main lobe to zero-degree of the target direction. Assume that the target is located within a fixed region (*e.g.*, directly facing the antenna array with an incidence angle of 0°), while the direction of non-target motion interference is unknown. Specifically, we direct the main lobe to the target direction (*i.e.*, $\theta_T = 0°$) while scanning the directions ranging from $-90°$ to $90°$ with beam nulls (at a step size of $1°$). We employ an optimization algorithm to find the optimum weight of DN-BF. The optimization function is as follows:

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}}(c_1 \cdot |\boldsymbol{w}^H \boldsymbol{a}(\theta_I)| - c_2 \cdot |\boldsymbol{w}^H \boldsymbol{a}(\theta_T)|) \quad (2)$$

where $\boldsymbol{w}^*$ denote the beamformer weight vector to be optimized, $(\cdot)^H$ is the conjugate transpose process, $|\boldsymbol{w}^H \boldsymbol{a}(\boldsymbol{\theta}_{(\cdot)})|$ represents the gain of a specific direction $\theta_{(\cdot)}$, c_1 and c_2 denote scale factors to constrain the main lobe steered towards θ_T. Here, we set the c_2 to about approximately ten times c_1.

Once the $\boldsymbol{w}^*$ is obtained, we multiply the denoised CSI signal by the corresponding weight of DN-BF for each direction. For each direction, DN-BF establishes a beam pattern that enhances the strength of reflected signals from the zero-degree target direction while suppressing signals from that interfering direction. By further analyzing the respiration energy of each scanned signal in different directions, we can adaptively find and eliminate the motion interference from interfering directions. While the DN-BF adjusts the positions of beam nulls and modifies the beam patterns, the angular resolution has undergone limited variations. Specifically, the angular resolution of conventional time-delay beamforming is approximately $\Delta_{3dB} \approx 2/(N \cdot d/\lambda) = 38.2°$ with half wavelength-spaced three antenna elements. In contrast, the DN-BF achieves -20 dB to -40 dB suppression in the noise direction through beam nulling, while maintaining angular resolution nearly unchanged (from 30.5° to 44°). After obtaining the DN-BF processed beamformed CSI for each direction, we calculate the unwrapped CSI phase information as candidate waveforms and select the most sensitive waveform for health state estimation.

Stage 3: Healthcare-related Services. After the above two stages, this step is straightforward. The robustness to motion interference can be employed for various WiFi healthcare applications, both for in-home and clinical healthcare scenarios. As illustrated in Fig. 2, for in-home regular healthcare scenarios, the patient may want to conduct their health status check without being interfered with by their family members or pets moving around. When it comes to clinical healthcare scenarios, extracting the target motion signal in dynamic environments will be beneficial for local wireless healthcare monitoring. Furthermore, the health information collected by target patients can ultimately serve as valuable reference information for public medical hospital allocation.

V. Case Study: In-Area Respiration Sensing for Target-Oriented Healthcare

In this section, we show some experimental results for different inter-user motion interference intensities and deployments of WiFi sensor nodes in WiFi-based respiration sensing.

As illustrated in Fig. 6 (c), we place the antennas of Tx and Rx at a distance of 1.5 m apart, with the target person being monitored in front of the Rx. We put the target person at $0°$ and the interferer at $30°$, $-45°$, $45°$, and $60°$, respectively. All the transceivers are off-the-shelf mini-PCs equipped with an Intel 5300 wireless NIC and are held up at a height of 100 cm, corresponding to the ergonomic sitting and breathing level of users.

In the first experiment, a non-target participant performs different types of activities (*i.e.*, keeping stationary, hand-waving, and stepping) to represent the three levels of motion interference intensity, and a target subject is sitting in front of the WiFi receiver array. The interfering activities are as follows:

- **Minor motion interference**: the non-target participant sits in close proximity to the target participant, with his/her subtle respiratory motions serving as the source of motion interference.
- **Moderate motion interference**: the non-target participant performs hand-waving as the motion interference, where his/her arm motion is towards the WiFi receiver.
- **Severe motion interference**: the non-target participant stands in close proximity to the target person and performs stepping interference involving both arm and leg movements simultaneously.

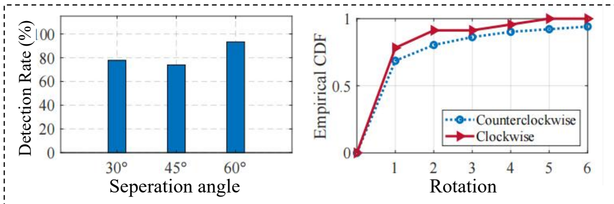
As illustrated in Fig. 6 (a), we achieve a median error lower than 0.5 bpm for all types of interference motion. However, it might be counterintuitive that the accuracy of moderate interference (hand-waving interference) is comparatively lower than that of severe interference (stepping interference). This might be attributed to the high similarity between CSI variations induced by hand-waving and respiration, which may result in respiration energy observed in both the target and interfering directions. We also demonstrate the efficacy of employing our proposed methods, *i.e.*, DN-BF and BDC. The absolute errors without the BDC for these three types of motion interference are 0.59 bpm, 0.51 bpm, and 0.23 bpm, respectively, while the mean absolute error without the DN-BF for these three types of motion interference is 0.72 bpm, 0.37 bpm, and 0.71 bpm, respectively. Compared with respiration monitoring with both BDC and DN-BF, the system performance in motion-interference scenarios declines significantly. In summary, all these results have demonstrated the effectiveness of the BDC and DN-BF for target-oriented respiration sensing.

To further evaluate the system's robustness across different WiFi sensor deployments, we perform experiments with different deployments and positions of WiFi sensor nodes. Specifically, we evaluate two primary scenarios: 1) the interferer

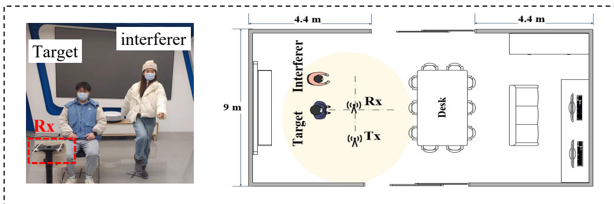
Ablation experiment of target-oriented spatial filer					
	Overall	Normal Conditions	Complex Conditions		
			Minor	Moderate	Severe
DN-BF(-)	0.72	0.37	0.75	1.29	0.71
BDC(-)	0.35	0.17	0.59	0.51	0.23
All	**0.28**	**0.19**	**0.27**	**0.42**	**0.41**

(–) represents removal for a certain processing.

(a)



(b) System performance under different deployments.



(c) Experimental setup

Fig. 6: Real-world experiments evaluating the effectiveness of target-oriented spatial filter: a) Ablation study of the target-oriented spatial filter; b) System performance under different WiFi sensor deployment; c) Experimental setup.

positioned at varying angles relative to the WiFi sensor and 2) the interferer positioned on either the left or right side of the sensing device.

In the first scenario, the interferer is placed at $30°$, $45°$, and $60°$. To maintain other factors constant, we instruct both the target person and the interferer to engage in natural breathing. As illustrated in Fig. 6 (b). The system errors decrease as the separation angle increases. When the subjects get closer, the interference nulling ability of DN-BF declines. The reason behind this is that when the direction of nulls is small enough, the main lobe width of DN-BF will not continue to shrink to ensure that the gain in the target direction is high enough to extract the target signal.

In the second scenario, the interferer is put at the same separation angle but on a different side of the WiFi receiver (*i.e.*, counterclockwise or clockwise). We vary the separation angle while keeping other factors unchanged (*i.e.*, $-45°$ and $45°$). The MAE under these settings is 0.38 bpm and 0.16 bpm for the left and right sides, respectively. Comparing the two experimental settings, the interferer is in the right direction, which leads to a comparatively weaker interference. This is because of the physical separation of the WiFi device transceiver. When the interferer is located away from the transmitter, the reflected signal caused by the interference exhibits a smaller magnitude, thereby leading to diminished interference to the system.

VI. Limitations, Challenges, and Open Issues

Although some of the motion interference issues in WiFi-based healthcare sensing have been discussed above, there still remain some challenges to be addressed as follows:

Co-directional Motion Interference: The key of our system is leveraging beamforming technology to extract the signal from the desired direction while suppressing the motion noises from other directions. However, an inherent characteristic of beamforming is that it cannot identify the motion noise from the co-direction of the target direction. When the interferer and the target person are in the same direction with respect to the antenna array, it is difficult to separate the signals of the target individual and interference. One potential method is the joint estimation of AoA-ToF (Angle of arrival-Time of Flight). By leveraging both angle and distance information, this method can differentiate signals from multiple sources, even when they are in the same direction. However, due to the limited antenna number of existing commodity WiFi devices, it may encounter challenges in generating high-resolution AoA-ToF maps.

Interference Management: In the proposed schemes, we have solely considered inter-user motion interference with a single target human scenario. When extending to other motion interference scenarios (*e.g.*, hybrid motion interference), further investigation is required to address the challenge of low resolution in WiFi signals, and countermeasures should be tailored accordingly based on the specific type of motion interference. Fortunately, thanks to the advancements in ISAC hardware and software platforms for WiFi systems, WiFi radars are equipped with more antennas. We expect WiFi sensing systems to achieve better anti-motion interference performance in the future with more hardware capabilities and high-quality CSI measurements.

Potential for Other Application Scenarios: This study has focused on evaluating the target-oriented sensing performance in a respiratory monitoring application, but it also has potential applications in various healthcare fields, such as sleep monitoring, chronic respiratory disease management, *etc*. These applications require consistent, long-term health monitoring but inevitably encounter motion interference from non-target individuals. By leveraging motion-interference filtering based on DN-BF, the system can focus on individuals within defined target areas, filter out extraneous motion, and achieve high accuracy and reliability performance even in complex, multi-person settings. Furthermore, as WiFi-based sensing technology advances with wider bandwidths and larger antenna arrays, the target-oriented sensing framework is expected to become more robust to resist motion interference in complex real-world scenarios.

VII. Conclusion

In this article, we propose an inter-user motion interference-tolerant (IMIT) framework for WiFi-based target-oriented healthcare sensing, which employs adaptive CSI beamforming as the inter-user motion interference filter. More specifically, we discussed the causative factors of performance degradation in typical interfering scenarios, including inter-user interference, self-motion interference, device motion interference, and hybrid motion interference. We outline the IMIT framework and pinpoint its enabling technologies and challenges. Case study experiments verify the feasibility and benefits of our proposed framework. We hope that our work can spur interest and fascinate the practical deployments of WiFi-based healthcare services.

VIII. Acknowledgements

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