

# Overview of Radar-Based Gait Parameter Estimation Techniques for Fall Risk Assessment

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**Abstract**— Current methods for fall risk assessment rely on Quantitative Gait Analysis (QGA) using costly optical tracking systems, which are often only available at specialized laboratories that may not be easily accessible to rural communities. Radar placed in a home or assisted living facility can acquire continuous ambulatory recordings over extended durations of a subject's natural gait and activity. Thus, radar-based QGA has the potential to capture day-to-day variations in gait, is time efficient and removes the burden for the subject to come to a clinic, providing a more realistic picture of older adults' mobility. Although there has been research on gait-related health monitoring, most of this work focuses on classification-based methods, while only a few consider gait parameter estimation. On the one hand, metrics that are accurately and easily computable from radar data have not been demonstrated to have an established correlation with fall risk or other medical conditions; on the other hand, the accuracy of radar-based estimates of gait parameters that are well-accepted by the medical community as indicators of fall risk have not been adequately validated. This paper provides an overview of emerging radar-based techniques for gait parameter estimation, especially with emphasis on those relevant to fall risk. A pilot study that compares the accuracy of estimating gait parameters from different radar data representations – in particular, the micro-Doppler signature and skeletal point estimates – is conducted based on validation against an 8-camera, marker-based optical tracking system. The results of pilot study are discussed to assess the current state-of-the-art in radar-based QGA and potential directions for future research that can improve radar-based gait parameter estimation accuracy.

**Index Terms**—Fall risk assessment, gait parameter estimation, micro-Doppler, radar, skeleton estimation

**Impact Statement**— Quantitative Gait Analysis (QGA) relies on expensive optical tracking systems in specialized laboratories, whereas radar-based in-home QGA can capture daily gait variations, providing more realistic, continuous assessment of mobility. [max 30 words]

## I. INTRODUCTION

**H**UMAN gait is an important health indicator, especially for older adults, who may increasingly experience issues with balance and stability as a normal part of the aging process. Monitoring of gait can provide early warning of diseases or important information on post-treatment recovery. As such, gait

parameter estimation is an important task for any remote health monitoring system installed either in-home or in an assisted living facility in support of aging-in-place. Falls especially remain a significant threat to the health of older adults: according to the U.S. Center for Disease Control, each year, roughly 1,800 older adults suffer fall-related fatalities in assisted living facilities [1]. Thus, fall prevention and fall risk assessments are critical to preventing debilitating injury and fall-related fatalities.

Falls often occur during walking [2]-[5] and although fall risk is influenced by a variety of intrinsic and extrinsic factors [6], gait and balance disorders have been consistently identified as one of the strongest risk factors. Not surprisingly, many studies suggest that gait features are associated with a history of falls and are good predictors of prospective falls [7]. Consequently, standardized gait assessments are commonly used in the clinical practice guidelines to evaluate and prevent fall risk [8]-[11]. Numerous approaches have been taken to quantify gait and its relation to falls. Clinical rating scales usually integrate a cumulative score based on performance across multiple tasks. Accordingly, they are useful in evaluating mobility limitations and fall risk, but do not identify the specific mechanics that are associated with falls. Moreover, they may lack of discriminant ability, especially in healthy populations that have not started to fall frequently [12].

Quantitative gait analysis (QGA) may not only provide an indication of an individual's risk of falling, but also highlight specific modifiable gait characteristics that can be targeted with interventions to reduce the risk of future falls. Gait assessment can be altered to increase the level of difficulty (e.g., dual-task paradigms, turning, backward walking, and walking at a fast pace). Current methods for fall risk assessment with QGA rely on gait parameters extracted from optoelectronic motion capture systems, such as Vicon, which utilize markers on the participant to accurately estimate the position vs. time of each marker with multiple cameras. Such optical tracking systems are currently used in most gait analysis laboratories for both clinical and research purposes and provide a “gold standard” for gait analysis [13]. However, reliance on motion-capture based QGA systems involves expensive equipment, raising the cost of health care, while not being readily accessible as they are few,

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predominantly operated by medical schools in large cities, and thus distant from rural populations. These barriers can result in infrequent assessments and delays in diagnosis, especially for underserved or low-income adults. Moreover, QGA labs are controlled environments that preclude the assessment of natural gait: people invariably alter their behavior when they know they are being observed. This phenomenon is known as the Hawthorne effect and has been shown to influence gait [14]. For example, in the presence of an observer, limping was less pronounced and double support time more symmetrical in the gait of lower limb prosthesis users [15].

As a result, there has recently been great interest in the development of in-home QGA to enable continuous monitoring of gait in an uncontrolled environment, paving the way for reduced health care costs, more widespread access to gait assessments, and improved health outcomes. Both wearable and camera-based systems have been proposed for fall risk assessment [16], while radio frequency (RF) sensing – or radar – is a more recently proposed, emerging modality due to its ability to operate ambiently and in a non-contact fashion from a distance without requiring any light [17][18]. This makes radar particularly well suited for monitoring in indoor settings, such as private homes and senior living communities, operating either in a stand-alone or complementary fashion with wearables, which may be forgotten to be worn, and cameras, which may not be preferred for ambient use as it may be intrusive of private moments and spaces. As such, radar can potentially offer continuous assessments even in sensitive settings without any burden on the user and operates ambiently without batteries. The RF emissions of typical radars are safe for humans, with levels at least 100 times less than that of a typical cell phone.

A radar placed in a home or assisted living facility can acquire continuous ambulatory recordings over extended durations of a subject's natural gait and activity. Radar-based QGA can capture day-to-day variations in gait, is time efficient and removes the burden for the subject to come to a clinic, providing a more realistic picture of older adults' mobility. This can aid in identifying psychological conditions, such as depression, which are marked by low activity levels, environmental factors that may be a cause of aberrations in gait, and early warning signs of neuromuscular disorders and potential fall risk – before a debilitating fall occurs.

Over the past decade, research on gait-related health monitoring with radar has focused on classification-based methods for fall detection [19]–[22], gait/activity recognition [23]–[34], aided/unaided ambulation discrimination [35]–[37], or detection of gait abnormalities [38]–[41]. However, there have been fewer works that consider gait parameter estimation for QGA. On the one hand, many metrics that are accurately and easily computable from radar data have not yet been demonstrated to have an established correlation with fall risk or other medical conditions. On the other hand, the accuracy of estimated gait parameters that are well-accepted by the medical community as indicators of fall risk have not been adequately validated. Often, many works report the accuracy of the

proposed radar-based estimation methods in comparison to the Kinect sensor or an assortment of web cameras; however, such markerless systems are more prone to significant estimation errors and thus offer inadequate assessment and benchmarking of true accuracy.

This paper provides an overview of emerging radar-based techniques for gait parameter estimation, especially with emphasis on those relevant to fall risk. The results of a pilot study comparing different radar-based estimation approaches are provided in conjunction with detailed discussion to provide comprehensive assessment of the current state-of-the-art and highlight areas requiring future research.

## II. RADAR-BASED GAIT PARAMETER ESTIMATION

The received signal of a typical frequency modulated continuous wave (FMCW) radar system for the backscatter from a point target is a time-shifted, frequency modulated version of the transmitted signal. Thus, the received backscatter,  $s(t)$ , from the entire human body can be represented as the superposition of reflections from each point on the surface of the body,

$$s(t) = \sum_{i=1}^K a_i e^{-j[2\pi f_0 t + \frac{4\pi}{\lambda} R_i(t)]} \quad (1)$$

where  $f_0$  is the center transmit frequency,  $\lambda$  is the wavelength,  $t$  is time,  $R_i(t)$  is the time-varying range of each point on the body to the radar transceiver, and  $a_i$  amplitude for the  $i^{th}$  point as computed from the radar range equation [42],

$$a_i = \frac{G\lambda\sqrt{P_i\sigma_i}}{(4\pi)^{3/2}R_i^2(t)\sqrt{L}} \quad (2)$$

Here  $G$  is the antenna gain,  $P_i$  is the transmitter power,  $\sigma_i$  is the radar cross section (RCS) for each point target, and  $L$  represents losses, such as electronic noise.

Nowadays many commercially available radar systems also have multiple channels, or elements in their antenna array, so that the received multi-channel RF data stream can be reshaped into a 3D array: fast-time (number of analog-digital converter samples)  $\times$  slow-time (number of pulses)  $\times$  channel number. If the radar system has both a vertical and horizontal linear array, then the resulting RF data stream can be formed into a 4D array of fast-time, slow-time, vertical and horizontal channels.

Using radar signal processing, various 2D data representations may be computed [42]–[44]: micro-Doppler ( $\mu$ D) signatures, range-Doppler (RD) and range-Angle (RA) maps. RD maps are computed by taking a 2D Fast Fourier Transform (FFT) of the slow-time/fast-time data matrix for a single array element, while RA maps are found by computing the direction of arrival (angle) of the radar backscatter using methods such as the Multiple Signal Classification (MUSIC) algorithm [45][46]. Application of MUSIC for each coherent processing interval (CPI) during which  $N$  pulses are transmitted

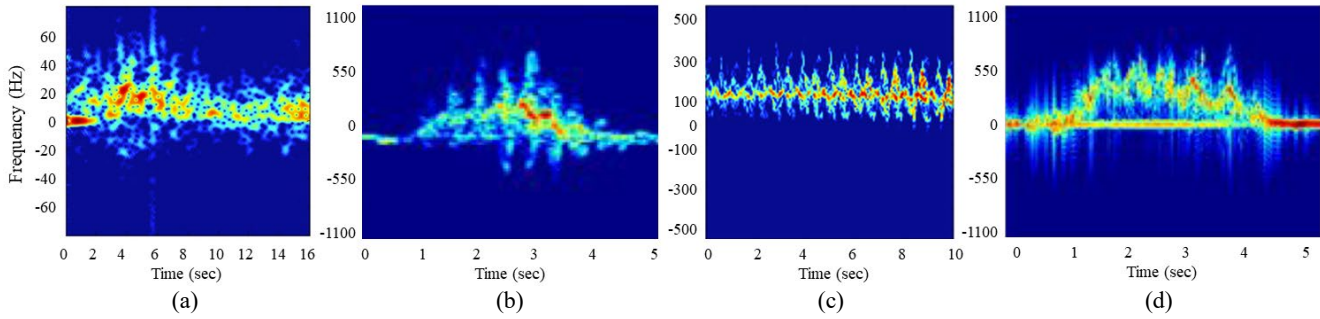


Figure 1. Micro-Doppler signatures of a person walking as acquired from (a) 5.8 GHz pulsed doppler (PD) radar, (b) 10 GHz ultra-wide band impulse radar (UWB-IR), (c) 24 GHz continuous wave (CW) radar, and (d) 77 GHz FMCW radar with 4 GHz bandwidth.

will result in a time-series of RA maps.

Most works on radar-based QGA derive the estimates from the radar  $\mu$ D signature [43], a representation of the velocity of the backscatter from each point of the body as a function of time. Micro-Doppler signatures are computed by applying a time-frequency transformation, such as the short-time Fourier Transform (STFT), across the slow-time samples of the radar data cube. To ensure that  $\mu$ D signatures are independent of the subject's range, cell averaging constant false alarm rate (CA-CFAR) detection [42] can be applied on RD maps to identify the range bins that include subject motion. Then, only these detected range bins are used in the computation of the  $\mu$ D signature.

The frequency, bandwidth and pulse repetition interval (PRI) of the transmitted signal can affect the accuracy of the gait parameter estimates derived from  $\mu$ D signatures. The depth resolution ( $\Delta r$ ) of an FMCW radar reflects the ability of the radar to differentiate between the radial distance, or slant range, between two point scatterers and is computed as  $\Delta r = c/2\beta$ , where  $c$  is the speed of light and  $\beta$  is the transmitted signal bandwidth. The velocity resolution  $\Delta v = \lambda/(N \cdot PRI)$ , where  $N$  is the number of pulses transmitted over a CPI. Thus, the higher the transmit frequency of the radar, the shorter the wavelength, and the smaller the differences in velocity that can be resolved. Note that range and velocity resolution differ from the size of the range and velocity bins, which indicate size of each pixel. The size of a range bin is given by  $r_b = (c/2)t_s$ , where  $t_s$  is the sampling interval of the analog-to-digital converter of the radar. The size of a velocity bin is computed as  $v_b = \lambda/(2 \cdot PRI \cdot N_{fft})$ , where  $N_{fft}$  is the number of FFT points utilized. The angular resolution of a multi-channel radar depends on the beamwidth of the main lobe of the antenna beam pattern, and can be computed as  $\theta = K\lambda/D$ , where  $K$  is the beamwidth factor and  $D$  is the size of the aperture. Beamforming techniques [47] can be utilized to form larger virtual arrays and improve the angular resolution of a radar.

The impact of different radar transceiver parameters may be observed from the sample  $\mu$ D signatures shown in Figure 1 for a person walking as acquired by four different radars: a 5.8 GHz pulsed doppler (PD) radar, 10 GHz ultra-wide band impulse radar (UWB-IR), 2.4 GHz continuous wave (CW) radar, and 77 GHz FMCW radar with 4 GHz bandwidth. The ground clutter

returns, which result from backscatter from stationary objects/surfaces in the environment, result in a horizontal line at 0 Hz. This is most clearly observed in the 77 GHz  $\mu$ D signature shown in Figure 1(d), where the oscillatory characteristics of the gait cycle in the human return can be clearly visually differentiated from the 0 Hz clutter line. These clutter returns can be filtered out using a Butterworth low pass filter or techniques such as Moving Target Indication (MTI) [42], as illustrated with the signatures of Figure 1(a)-(c).

The torso response is often the body part that results in the strongest backscatter and may be identified as a reddish sinusoidal curve in the  $\mu$ D signature. At low frequencies, such as the 5.8 GHz, the periodicities of the gait cycle are not as clearly observed as in the higher frequencies. Moreover, the average velocity of the gait signature appears at lower Doppler shift frequencies when the transmit frequency is lower. This increases the likelihood of the clutter returns masking the low frequency components of the gait signature – an effect that can degrade the accuracy of gait parameter estimates or gait classification algorithms. While millimeter wave frequency transmissions result in data with the most evident limb trajectories, higher frequencies also suffer from more significant atmospheric attenuation, as may be seen by the inverse relationship between the signal amplitude  $a_i$  and frequency (since  $f = c/\lambda$ ) captured in Eq. (2).

The pulse repetition frequency (PRF), which is the inverse of the PRI, also determines the maximum Doppler shift that can be acquired by a radar unambiguously. If the PRF is lower than the Doppler shift incurred by the maximum speed of movement, aliasing occurs in which the high frequency parts of the signature will wrap around to the bottom of the image. Such effects are highly detrimental to gait analysis algorithms, which typically rely on capture of unaliased  $\mu$ D signatures.

Note that as the cost of a radar system often depends on the transmit frequency, bandwidth and number of antenna elements in azimuth and elevation, an important question that merits further investigation is what the minimum transmission requirements are to achieve a certain level of accuracy in gait parameter estimates for QGA in real-world conditions. The radar transmission also affects the sample size in each of the dimensions of the radar data tensor; thus, the transmission parameters also influence computational complexity and may



be a limiting factor in situations requiring real-time QGA.

A key limitation of  $\mu$ D-based gait parameter estimation is that the  $\mu$ D signatures represent the aggregate backscatter from the entire human body – not a specific body part or joint. This makes recent advancements in RF skeleton estimation interesting to consider from the perspective of QGA. However, most RF skeleton estimation methods utilize deep neural networks (DNNs) to learn a mapping between various types of radar representations to skeletal key points. Thus, the methods are very data greedy and have been primarily considered in the broad context of monitoring activities of daily living – a task that does not require the same level of estimation accuracy as gait parameter estimation for QGA. The pilot study presented in Section IV provides a gold standard comparison of estimation accuracy from both  $\mu$ D signatures and RF skeletons under a moderate amount of data. Relevant results from the literature are discussed next.

#### A. QGA using RF Micro-Doppler Signatures

Early works on radar-based gait analysis [48] [49] focused on the estimation of walking speed by averaging the speed corresponding the strongest (peak) return in the  $\mu$ D signature, which typically results from torso backscatter. Later, when it was shown that backscatter from a person could be well approximated by Eq. (1) utilizing superposition [50] [51], biomechanical models – such as the Boulic walking model [52], which provided parametric equations and graphs representing body part trajectories and joint angles – were exploited to estimate the height and speed of a person walking [53] [54].

While early works did not involve gold standard comparisons, in 2014, a study [55] was conducted that investigated the estimation accuracy of walking speed and step time, comparing the estimation accuracy attained over a 17-ft walkway using a 5.8 GHz foot-level and torso-level radar with that of a Vicon-based optical tracking system. Excellent agreement between radar and Vicon-based estimates were found for step time estimation using the foot-level radar; however, for walking speed, the impact of aspect angle on velocity-estimates was noted as a cause for an offset between radar and Vicon-based estimates. This offset was less in the torso-level radar data and more pronounced in the foot-level radar data. This result is not surprising, considering that the Doppler shift is proportional to radial velocity, not absolute velocity.

To mitigate the impact of aspect angle in QGA methods based solely on  $\mu$ D signatures, researchers have proposed utilizing radar systems for gait analysis in hallways, which would preclude significant angular deviation from the radar line of sight. For example, in [56], walking speed, step points, step time, step length, and step count are estimated from a radar monitoring a 14 m. hallway. Alternatively, [57] has proposed utilizing radar for walking tests administered by physical therapists, whereby the subject would walk along a straight path away from the radar, turn around, and then walk back towards the radar. Analysis of radar  $\mu$ D signatures was utilized to segment the data into three segments: an acceleration zone, a

measured-gait zone, and a deceleration zone. The resulting gait speed estimate was validated against a Vicon motion capture system and found to have an error of 0.076 m/s.

More advanced signal processing techniques have also been proposed to track limb motion during ambulation and enable angle-agnostic  $\mu$ D-based QGA. In [58], a 1-D block processing method is proposed to use CW radar to track the arm, elbow, hand, torso, knees, calf or ankle under various types of walking – walking without hands moving and walking with one arm or both arms swinging. The maximum speed of tracked body parts is reported in comparison with that obtained using the Boulic model. While the method appeared effective in extracting lower limb motion during ambulation, tracking the hand and arm movements was less reliable. Aside from CW radar, researchers have also proposed using Stepped-Frequency CW (SFCW) radar with a rapid pulse repetition frequency (PRF) to track fast motions of various parts of the body [59].

Despite the limitations of angular dependence,  $\mu$ D-based QGA has been shown to have great potential in extracting a much broader range of gait parameters than just gait speed. In [60], an ultrawide-band impulse radar (IR-UWB) was used to estimate not just walking speed, but also step length, cadence, stride length, step frequency, lower limb orientation, and total traversed distance. The IR-UWB radar estimates were seen to correspond well with estimates obtained from the accelerometer and gyroscopic sensors on a smartphone. Using the peak of the  $\mu$ D signature as reflective of the trunk velocity profile, [61] compared the estimation accuracy of stride time, step time, step length, swing time and stance time for a 24 GHz CW radar and Vicon systems. A comparison of the impact of having a single versus multi-channel FMCW radar system on an analysis of gait variability is given in [62], while also showing the assessment accuracy in comparison with Vicon data. This work was extended in [63] to consider step time variability via radar data acquired over continuous streams of activity data collected in an unconstrained environment. The continuous data is segmented and sequentially classified to extract the intervals over which the subjects are walking. The impact of segmentation accuracy on step time variability is discussed.

While these aforementioned works focused on estimation based on the trunk profile, other works have proposed the estimation of gait parameters from the envelopes of the  $\mu$ D signatures. The envelopes represent the speed of maximum (forward or backward) movement on the body, which is typically caused by the movement of the feet. Thus, without explicitly tracking the feet, several researchers [64] have estimated a broader range of gait parameters by extracting envelopes of the toe, ankle and knee from the  $\mu$ D signature: stride time, stance time, flight time, step time, cadence, stride length, step length, maximal foot velocity, maximal ankle velocity, maximal knee velocity, and time instant of maximal knee velocity. Based on comparisons against a 3D motion capture system with 12 infrared cameras, radar-based estimates were found to match well for most of the gait parameters extracted. Furthermore, it was proposed that symmetry (or

asymmetry) in the micro-Doppler signature could be characterized as an indicator of gait abnormality [39].

Similarly, simulation-based studies [65][66] have proposed extraction of twelve different gait metrics from the torso profile and envelopes of the  $\mu$ D signature, including 1) mean body velocity (gait speed), 2) degree of variation in body velocities, 3) maximum body velocity, 4) minimum body velocity, 5) mean leg velocity in swing phase, 6) degree of variation of leg velocities in swing phase, 7) maximum leg velocity, 8) minimum leg velocity in swing phase, 9) mean leg velocity in stance phase, 10) degree of variation of leg velocity in stance phase, 11) maximum leg velocity in stance phase, and 12) minimum leg velocity. These metrics were then utilized to categorize participants as fallers or non-fallers.

Subsequently, a study [67][68] experimentally validating these simulation results was conducted by recruiting older adults aged 65 and above, who are able to walk without assistance of another person or walking aide, from a senior day care center and rural community center. The participants were given a questionnaire about their fall history within the past year, based upon which they were divided into one group of non-fallers (19 people, mean age 78.8) and fallers (14 people, mean age 82.5). Participants were then asked to walk for 10 meters, during which time their gait was measured using a micro-Doppler radar. Four gait parameters (1, 5, 6, 10) were extracted from the micro-Doppler signatures and used to classify participants as fallers or non-fallers with an accuracy of 78.8%. In another study [68] involving 74 older adults aged 75 years and above, a subset of these radar-based gait parameters (1, 5, 6, 7, 9, and 10) were also shown to correlate well with the results of four cognitive function tests – the Mini Mental State Examination (MMSE), Digit Symbol Substitution Test (DSST), Scenery Picture Memory Test (SPMT), and Verbal Fluency Test (VFT) – and were used to classify participants according to high / low cognitive function.

More recently, automation of the Timed Up and Go (TUG) test, which is an established, standardized test used in clinical practice for assessing mobility and fall risk, has been proposed using radar. In [69], an ultra-wide band (UWB) radar was utilized to segment and estimate the stride length during execution of a TUG test, comparing the accuracy of radar estimates against those acquired from sensors placed in the insole of a shoe. This study found that the risk scores obtained using an insole containing three force sensors and y-axis of acceleration were comparable to that attained using a single radar and two force sensors. In another study [70], also using UWB, measurements of walking duration, turning duration, and gait speed acquired during a TUG test were shown to correlate well to measurements acquired from a video-based system.

In 2023, the first radar-based system to fully automate the TUG test measurements was proposed [71] in which data from a CW Doppler radar was processed to segment the continuous data stream according to “transfer” and “walk” phases as well as “walk” and “turn” phases. Afterwards, gait parameters, such as the number of steps, step time, gait cycle duration, swing time, average walking speed, cadence, TUG walking speed duration,

TUG duration, step time, and stride length were computed from the radar micro-Doppler signature. The study was conducted on 26 healthy subjects, aged between 22 and 60, who performed three TUG trials at slow, normal and fast speed, leading to a total of 9 trials per subject. Data was acquired simultaneously from the CW radar and a Vicon motion capture system to validate radar-based measurements. High correlation coefficients were obtained for the torso speed, limb oscillations, initial and final indices of the TUG phases and extracted gait parameters. As such, this work represents the first to show experimental results indicating the feasibility of automating TUG tests using radar.

### B. QGA using Joint RF Data Representations

Although  $\mu$ D-based QGA has the benefit of being applicable to any kind of radar, including the lowest-cost, least complex CW radars, the limitations brought by aspect angle dependency and the increasing availability of multi-channel RF transceivers at lower and lower costs has driven research into QGA based on joint RF domain representations, such as the radar data cube, which captures not just velocity information, but also information about range and angle as a function of time. Techniques such as multi-dimensional principal component analysis (PCA) have been proposed for exploiting the radar data cube for activity recognition [72] and fall detection [73]. In [74], a joint domain multi-input, multi-task learning (JD-MIMTL) network is proposed that takes not just stacked snapshots of  $\mu$ D, but also range-Doppler and range-Angle maps as input to identify when a person is walking and subsequently extract the torso velocity and acceleration to assess gait variability.

In [75], a FMCW radar is used to track subjects [76] as they move freely in the home, extracting the stable phase of walking intervals (which excludes acceleration and deceleration phases), so as to monitor the gait speed of 50 participants, with and without Parkinson’s disease, for up to a year. The study showed that at-home gait speed, as estimated using radar, strongly correlates with gold-standard assessments of Parkinson’s disease, such as the Movement Disorder Society-Sponsored Revision of the Unified Parkinson’s Disease Rating Scale (MDS-UPDRS) part III sub-score and total score.

Beyond just estimation of gait speed and torso profile, several studies have also exploited the range, angle and velocity information of the radar to improve limb tracking. For example, [77] separately recognized the legs in the range-Doppler map and extracted the range and velocity profile for each leg. Using these profiles, stride time, stance time, flight time, step time, cadence, maximum foot velocity and its interval were estimated. A new metric, the Gait Asymmetry Indicator (GAI), computed as

$$GAI = \left| \frac{MFV_R}{MFV_L} - 1 \right| \quad (3)$$

where  $MFV_L$  and  $MFV_R$  represents the maximum foot velocity of the left (L) and right (R) legs, respectively, was proposed to detect gait abnormality. The results were validated through

comparison with Inertial Measurement Unit (IMU) data over 15 participants in 4 scenarios (walking, running, left leg limping, and right leg limping) using the intraclass correlation value, which showed good agreement except for flight time.

Another study [78] utilizing synthetic range-Doppler versus time data simulated from a skeletal model proposes trajectory tracking using Kalman filtering and weighted joint nearest neighbor algorithm for data association. Trajectory tracking accuracies ranging of as much as 99.6% is reported, while the estimates of kinematic gait features – such as step length, stride speed, stride frequency, gait phase, step length symmetry, phase symmetry, acceleration time constant of forearms, and skewness of thighs – are reported to have 91.9% - 93.8% accuracy. While limb tracking techniques show promise, the accuracy of current methods on real radar data has not yet been adequately evaluated. Advancement of more effective methods for limb tracking remains an open area of research.

### C. QGA using RF Skeletons

The task of tracking limbs through micro-Doppler data encounters obstacles due to human motion's intricate and dynamic properties, where distinguishing between overlapping signals and the slight movements of minor limbs poses accuracy challenges. Yet, the potential of leveraging high-dimensional RF data (spanning range, angle, and Doppler) for radar-based pose estimation in limb motion tracking is promising. Progress in signal processing and machine learning, particularly with the integration of Convolutional Neural Networks (CNNs), enhances accuracy and the capacity to detect minor movements, bringing non-invasive, real-time limb tracking closer to reality.

Initially explored with the proposal of RF-Capture [79] in 2015, radar-based human skeleton estimation utilizes 5.4 to 7.2 GHz FMCW signals via an antenna array to detect coarse body part positions, subsequently reconstructing a human figure by piecing together these detected parts. In 2018, RF-Pose3D [80] advanced this framework by employing a T-shaped 12-element antenna array for FMCW signal transmission and reception at a 6.3 GHz center frequency and 1.8 GHz bandwidth. This system feeds range-azimuth and range-elevation heatmaps into a Resnet-based encoder neural network, coupled with 12 camera nodes capturing RGB video to collect label key points from OpenPose for training a region proposal network (RPN) and a ResNet-architecture CNN. This network focuses on RF data from individual persons to extract 3D skeletons from regions of interest, reporting average localization errors of 4.2, 4.0, and 4.9 cm in the x, y, z axes, respectively, with OpenPose estimated key points. Despite its groundbreaking demonstration of RF skeleton estimation's feasibility, the method's reliance on over 17 million data samples and 16 hours of recordings underscored its significant data and computational demands, limiting practical application.

In 2020, mmPose [81] was proposed, which predicted more than 15 joints using two specially oriented IWR1443 radars. This method, feeding point clouds into a bifurcated CNN, did not utilize the radar's Doppler and signal intensity data, leading to jitter in skeleton animation. Attempts in 2022 with additional

filters [82] sought to reduce jitter for a more stable skeleton representation but did not fundamentally enhance accuracy. In 2021, another approach, MARS [83], was proposed, which employed IWR1443 radar and standard software for point cloud data, including Doppler and intensity information, reporting average MAE of 5.8cm accuracies in 19-point predictions compared to Microsoft Kinect v2 camera estimates. They further investigated joint angle estimation from the predicted skeleton and reported the average MAE of MARS in estimating left elbow angle, right elbow angle, left knee angle, and right knee angles are 12°, 13°, 7°, and 6°, respectively.

In recent years, there has been a significant surge in publications focused on mm-wave-based human pose estimation [84-92]. Generally, these studies employ radar-generated range-azimuth and range-elevation heatmaps, with some also incorporating radar point clouds, as data inputs for training their deep neural network (DNN) models. For validating their findings, the bulk of these studies have predominantly leaned on either the Kinect system or the multi-camera-based OpenPose model for ground truth. This approach presents substantial challenges in the realm of RF skeleton estimation. On one hand, the Kinect system, when employed as a benchmark for ground truth, is problematic due to its considerable errors in skeleton tracking. One study [93] showed that Kinect tends to provide an oversimplified version of the actual skeleton, with its estimates often deviating from those obtained through marker-based tracking methods. On the other hand, systems employing multiple cameras, such as OpenPose, introduce their own complexities. While Kinect's limitations stem from its inherent technology, the use of OpenPose, which relies on a multi-camera setup, is cumbersome and less practical for deployment. Furthermore, reliance on OpenPose has been shown [94] to introduce specific inaccuracies, including consistent biases in the estimation of knee and ankle joints, and relative biases in trunk and hip joints, in comparison to the estimations derived from optoelectronics motion capture systems, a more precise skeletal tracking method.

Hence, current QGA using RF skeleton has been limited to only estimating the skeleton coordinates. These efforts are constrained by key challenges, including the poor elevation angular resolution of the available off-the-shelf RF sensors, inappropriate use of Kinect for ground truth due to significant estimation errors, the impracticality of bulky multi-camera systems, and inaccuracies introduced by relying on the OpenPose model. Moreover, the dependency on complex, data-intensive models necessitates the exploration of more efficient models requiring less data, crucial for enabling practical skeletal estimation on mobile computing platforms.

## III. PILOT STUDY

To evaluate and compare different radar-based QGA techniques, a pilot study was conducted in which both radar and motion capture data were simultaneously acquired from participants who walked back and forth in an indoor lab at the University of Alabama.



### A. Experimental Design and Data Collection

Five healthy, right-foot males ( $25.6 \pm 1.9$  years,  $70.6 \pm 17.5$  kg,  $1.75 \pm 0.093$  m) completed the experiment. All participants (i) had no known history of neurological or musculoskeletal disorders; (ii) were naïve to the experimental conditions; (iii) had a normal or corrected-to-normal vision. Study procedures were approved by the Institutional Review Board at the University of Alabama under Protocols #18-06-1271, #21-10-5055 and #23-04-6553.

The RF data were acquired using a Texas Instruments (TI) IWR2243 Cascade radar, operating in the 77 GHz - 81 GHz frequency band with 12 Tx and 16 Rx antennas, positioned at the start of the walkway at about 1 meter height and aligned with the direction of walking, as shown in Figure 2. The TI radar was configured to utilize Time Division Multiplexing (TDM) to create 192 virtual Multi-Input Multi-Output (MIMO) channels. Out of these, 58 elements overlap in the azimuth plane, leaving only 86 non-overlapping channels designated for azimuth virtual antennas. Regarding the elevation, there are 7 elevation planes comprise an aperture size of  $6 \lambda/2$ . However, within this aperture, 3 planes are empty, and only 4 active elements/channels are allocated for elevation measurements. Additionally, there are 44 redundant elements in the elevation that do not comprise aperture larger than  $6 \lambda/2$ , therefore remain unused. Here  $\lambda$  is the wavelength of the transmitted signal. Figure 3 illustrates the virtual antenna array for this radar. Each radar chirp was comprised of 256 analog-to-digital

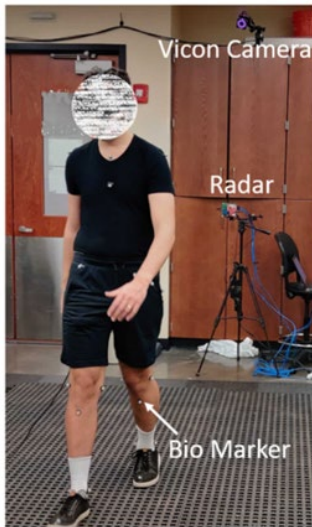


Figure 2. Experimental setup during data acquisition.

converter (ADC) samples, with a total of 128 chirp-loops per frame being transmitted. Consequently, the raw ADC data was organized into range-azimuth ( $256 \times 86$ ), range-elevation ( $256 \times 7$ ), and range-Doppler ( $256 \times 128$ ) planes.

Participants walked for five minutes at self-selected speed up and down a 6-meter walkway. A total of 41 reflective markers (MRKs) were attached to the whole body to record 3-D position data with an 8-camera motion capture system at a sample frequency of 100 Hz (NEXUS software and VERO infra-red Cameras, Vicon Motion Systems). To establish basic synchronization between the two recording systems, we initiated recordings simultaneously with a voice command while participants performed a fast "air punching" movement, clearly detected by both systems. Subsequently, we identified the radar frame displaying this rapid movement from the radar range-Doppler maps. Similarly, we pinpointed the frame in the Vicon skeleton data showing the hand punching forward. By aligning these two frames, we synchronized the two systems. Given that the radar operates at 10Hz and Vicon operates at 100Hz, we down sampled the Vicon frame to match the radar frame rate, ensuring we have a ground truth Vicon frame for each radar frame.

### B. RF Skeleton Estimation under Limited Data

In this work, we consider RF skeleton estimation when a limited amount of data is available for training. To quantify the estimation uncertainty due to the trained deep neural network (DNN) utilized for skeleton estimation versus other sources of estimation error, such as the resolution of the RF sensor or real-world effects, such as multipath reflections, we compare the skeleton estimation accuracy obtained when using simulated (SkelS) versus real (SkelR) RF data. In particular, we synthesize [95]-[97] the expected radar return using eq. (1) and eq. (2), where the time-varying ranges  $R_i$  to the  $i^{th}$  point are derived from the concurrently acquired Vicon motion capture measurements. When generating the simulated data, we deliberately restricted ourselves to using only 20 azimuth antenna elements/planes instead of the full 86 elements found in the real radar. This choice was made because the azimuth angular resolution in the real data is already quite high, enabling the deep neural network (DNN) model to effectively learn from it. Consequently, we reduced the number of azimuth antenna elements in the simulation to avoid generating an overwhelming amount of data. Conversely, we used 7 elevation planes with a  $6 \lambda/2$  aperture, ensuring no empty elements. This provides finer angular resolution in elevation compared to the real data's 4 elevation channels. Pre-training with this higher-

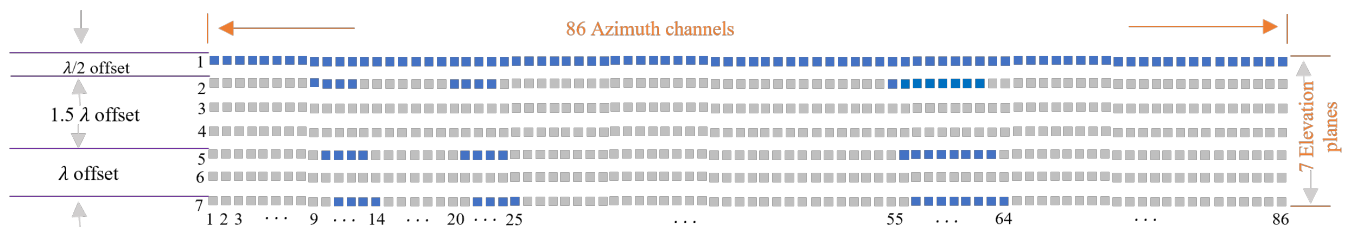


Figure 3: Virtual antenna array for TI AWR 2243 cascade radar.

resolution data helps set DNN weights at favorable local minima, improving feature representation learning during fine-tuning with coarse-resolution real data.

To reduce the dimensionality of both the measured and simulated RF data so that the resulting DNN for skeleton estimation is less complex and requires less data for training, we developed a 'max per range bin' and 'max per angle bin' method to capture the main features from the RF heatmaps. As the name suggests, this process finds the maximum intensity value at each range/angle bin to capture the variations of the return signal's strength over range and angle bins. This approach offers several benefits: first, it enables the representation of a 2D heatmap with just two vectors. For example, a 256x256 range-azimuth heatmap can be condensed into a 256x2 size array. Here, one vector represents the maximum per range bin (256x1), and the other captures the maximum per azimuth angle bin (256x1), markedly simplifying the challenge of managing extensive data matrices in DNNs. Consequently, for a set comprising both range-azimuth and range-elevation heatmaps, the result is a compact array sized 256x4. Second, this approach accurately maintains the gross velocity information by correctly capturing the movement of the target's peaks from one frame to the next. Third, as the dimensionality of the data is reduced, it enables a simpler neural network to effectively extract the necessary information for determining range, azimuth, and elevation. Thus, after aggregating all frames, the data's total size becomes 27,408x256x4. This is subsequently reshaped to 2,284x12x256x4 to incorporate the time dimension, the size of which was determined through empirical methods.

Next, a lightweight 3D CNN + Long Short-Term Memory (LSTM) model is designed to capture both the temporal and spatial characteristics for predicting the 3D coordinates of 14 skeleton joints. The architecture is comprised of a 3D convolutional layer, followed by batch normalization, max

pooling, dropout, and two bi-directional LSTM layers. It culminates in a time-distributed dense layer equipped with 42 neurons (reflecting 14 joints times 3 coordinates per joint) and employs a linear activation function.

The Huber loss function [98]

$$L\delta(y, f(x)) = \begin{cases} \frac{1}{2}(y - f(x))^2, & \text{for } |y - f(x)| \leq \delta, \\ \delta|y - f(x)| - \frac{\delta^2}{2}, & \text{otherwise} \end{cases} \quad (3)$$

is utilized for model optimization. It offers robust regression by being less affected by data outliers compared to the squared error loss. The Huber loss switches between Mean Squared Error (MSE) for small prediction errors and Mean Absolute Error (MAE) for large prediction errors, with the switch occurring at a specified threshold, delta ( $\delta$ ). When the prediction error is within the delta range, it utilizes MSE, which penalizes small errors more heavily and aids in fine-tuning the model's predictions. If the error exceeds delta, indicating a potentially large or outlier error, it uses MAE, which treats all errors linearly, thereby reducing the impact of outliers. This creates a more robust model by combining the sensitivity of MSE to small errors with the outlier resistance of MAE for large errors. For this key point regression model,  $\delta=1$  was used.

Among other hyperparameters, a learning rate of 0.0021, batch size of 32, and the model was trained for 80 epochs. The training was conducted using a leave-one-out approach, which was applied across the data from all subjects. On average, each subject's data consisted of approximately 5,600 pairs of radar frames. For every frame, the model was designed to predict 42 key points.

Initially, the model was trained and tested with simulated data with a leave-one-subject-out method, resulting in Mean Absolute Errors (MAE) of 3.15 cm for the medio-lateral (ML) axis, 4.37 cm for the vertical (V) axis, and 1.4 cm for the antero-

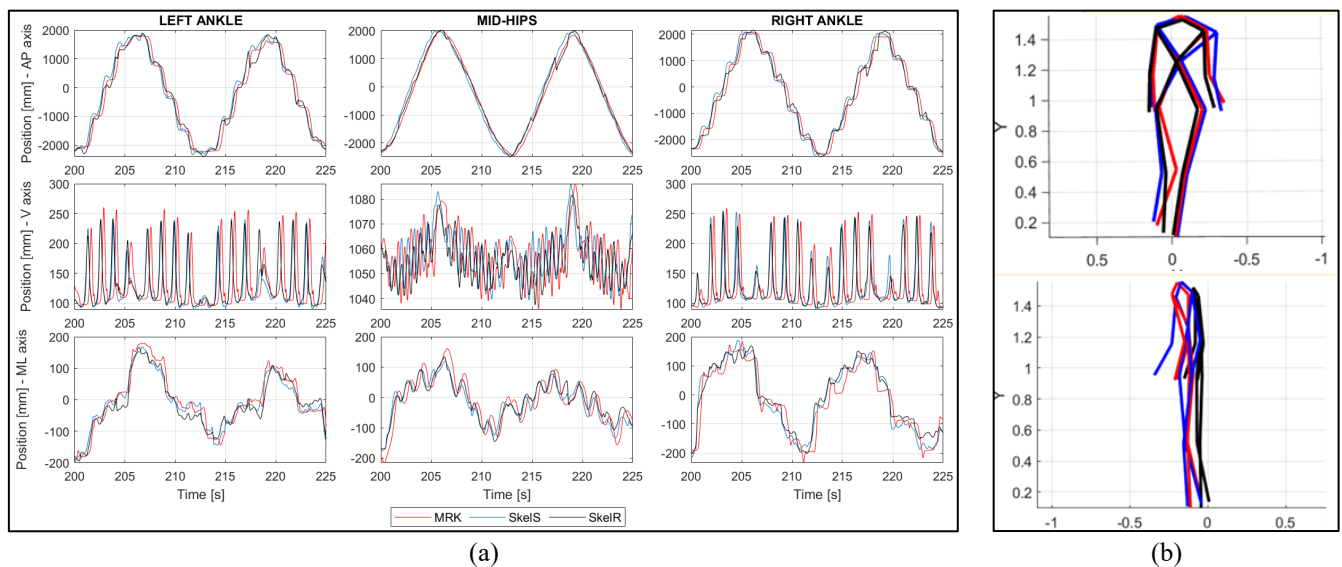


Figure 4. (a) Representative trajectories of the left ankle, right ankle, and midpoint of the hips along the Antero-Posterior (AP), Medio-Lateral (ML), and Vertical (V) axes for the three measurement systems. (b) Frontal and sagittal views of the 3D skeleton reconstruction of the three measurement systems for a single time frame. Motion capture (MRK, red line), Skeleton from simulated radar data (SkelS, blue line), and Skeleton from real radar data (SkelR, black line).



posterior (AP) axis. Subsequently, when this model pre-trained using simulated data was further refined (fine-tuned) using measured radar data, the MAEs increased to 5.63 cm for the ML axis, 7.30 cm for the V axis, and 7.81 cm for the AP axis. After predicting the RF based skeleton trajectories for all subjects, we increased its sampling rate to 100 Hz using linear interpolation. This adjustment was made to align the RF based skeleton trajectories with the original frame rate of the Vicon system, which operates at 100 Hz. It's worth noting that interpolation wasn't necessary for the Vicon data itself, given its native sampling rate of 100 Hz.

Figure 4(a) illustrates the 3D trajectories of the midpoint between the hips, left ankle, and right ankle extrapolated from the simulated radar data (SkelS), the actual radar data (SkelR), and the motion capture data (MRK) during four laps of a representative subject's trial. Figure 4(b) illustrates the reconstructed skeleton from the three measurement systems for a single time frame.

It's important to note that, for this application, minor misalignment between the RF and Vicon trajectories wasn't a significant concern. Our focus was primarily on gathering discrete gait parameters, such as step time and step length, by considering the time difference between corresponding points in each system.

### C. Data analysis for gold standard comparison

High-frequency related noise was removed from position data estimated with markers' coordinates (MRK), RF skeleton

from real data (SkelR), and RF skeleton from simulated data (SkelS) by low-pass filtering at 10 Hz (zero-lag, fourth-order Butterworth low-pass filter). For MRK, heel strikes were estimated by finding the farthest anterior position of the heels position relative to the sacrum. For SkelR and SkelS, heel strikes were estimated by finding the farthest anterior position of the ankles position relative to the mid-point of the hips. Step length was estimated as the absolute distance in the AP direction of the ankle markers from heel-strike to heel-strike.

The  $\mu D$  signature was computed as in our previous works [62][63]. The trunk radial velocity ( $V_{RF}$ ) was estimated by finding the peak  $\mu D$  signature intensity, which indicates the highest reflected energy. Indeed, it can be assumed that the strongest signal in the  $\mu D$  signature is due to the trunk motion, as the trunk comprises the largest radar cross-section of the body. High-frequency noise was removed by low-pass filtering  $V_{RF}$  data at 5 Hz [61]. Trunk acceleration was calculated as the first derivative of  $V_{RF}$  using a central finite difference method. Heel strikes were estimated by finding the zero-crossing points of the trunk acceleration curve, after low-pass filtering at 2 Hz [99]. The absolute value of  $V_{RF}$  was subdivided into steps. Step length was estimated as the area under the curve of  $V_{RF}$  over a step cycle.

For each run, the middle 5 steps were included in the analysis to ensure a steady walking state. For all methods, step time was computed as the time interval between consecutive heel strikes. Then, step time (ST), step length (SL), and their variabilities

TABLE I  
CONCURRENT VALIDITY

Variable	MRK Vs. $\mu D$			MRK Vs. SkelR			MRK Vs. SkelS		
	MD (Mean $\pm$ STD)	MPD [%] (Mean $\pm$ SD)	LOA [%]	MD (Mean $\pm$ STD)	MPD [%] (Mean $\pm$ SD)	LOA [%]	MD (Mean $\pm$ STD)	MPD [%] (Mean $\pm$ SD)	LOA [%]
ST [s]	0.007 $\pm$ 0.011	1.00 $\pm$ 1.71	3.3	-0.004 $\pm$ 0.007	-0.54 $\pm$ 1.09	2.1	-0.001 $\pm$ 0.005	-0.12 $\pm$ 0.76	1.5
SL [m]	-0.068 $\pm$ 0.022	-13.03 $\pm$ 4.52	8.9	0.010 $\pm$ 0.006	1.84 $\pm$ 1.05	2.0	0.005 $\pm$ 0.004	0.90 $\pm$ 0.72	1.4
STV [%]	10.79 $\pm$ 3.87	105.65 $\pm$ 33.74	66.1	12.29 $\pm$ 2.57	113.59 $\pm$ 9.06	17.8	8.85 $\pm$ 1.77	97.95 $\pm$ 26.51	52.0
SLV [%]	11.70 $\pm$ 4.17	95.13 $\pm$ 19.17	37.6	23.74 $\pm$ 5.72	130.35 $\pm$ 16.53	32.4	12.65 $\pm$ 0.94	101.58 $\pm$ 9.49	18.6

Measurement method: Markers (MRK), RF micro doppler ( $\mu D$ ), RF skeleton from real data (SkelR), RF skeleton from simulated data (SkelS). Gait Parameters: Stride Time (ST), Step Length (SL), ST Variability (STV), and SL Variability (SLV).

Concurrent Validity: Mean difference (MD), mean percentage difference (MPD), and 95% ratio limits of agreement (LOA) between the gait parameters obtained with the MRK and the three RF methods. A positive sign indicates larger values for the RF method.

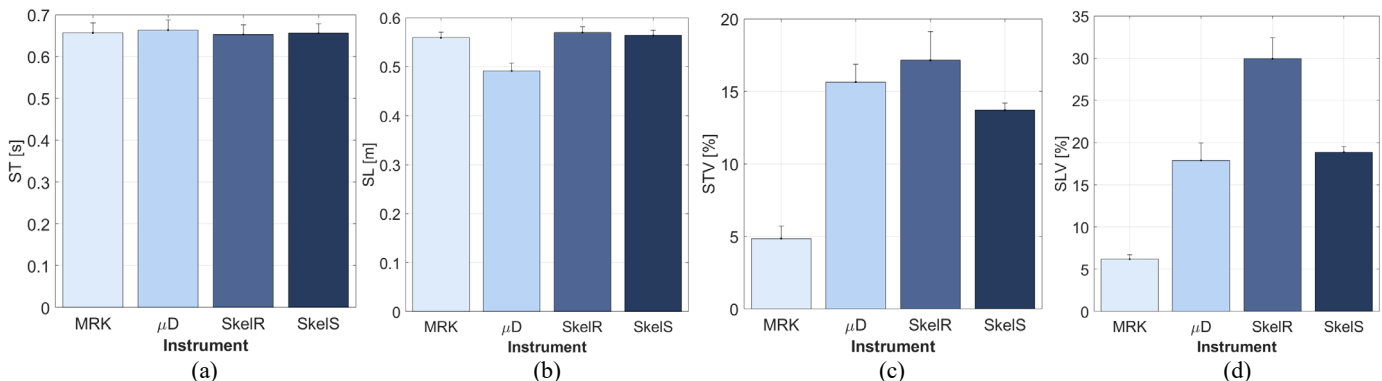


Figure 5: (a) Stride Time (ST), (b) Step Length (SL), (c) ST Variability (STV), and (d) SL Variability (SLV) obtained for Markers (MRK), RF micro doppler ( $\mu D$ ), RF skeleton from real data (SkelR), RF skeleton from simulated data (SkelS). Bars refer to the standard error.

(STV, SLV) were defined as the mean and the coefficient of variation of all accounted steps over the five minutes of walking. The coefficient of variation was computed as the percentage of the ratio between standard deviation and mean value. Differences between the MRK method and the three types of RF methods were expressed as mean of the differences (MD), mean percent difference (MPD), and 95% ratio limits of agreement (LOA). LOA was calculated as 1.96 times the standard deviation of MPD.  $|\text{MPD}+\text{LOA}|$  values  $>50\%$  were interpreted as poor,  $10\%–50\%$  as moderate,  $5\%–10\%$  as good, and  $<5\%$  as excellent agreement [100].

#### D. Results

Figure 5 shows the mean and standard deviation of the outcome variables extracted from each measuring system (i.e., MRK,  $\mu\text{D}$ , SkelR, SkelS). Table 1 reports the summary metrics for the differences between the gait parameters extracted with MRK and each RF method.

Independently by the RF method used, ST showed excellent agreement ( $|\text{MD}|<0.007\text{s}$ ;  $|\text{MPD}+\text{LOA}|<3.3\%$ ) with the  $\mu\text{D}$  method overestimating ST while both skeleton methods slightly underestimating ST. SL showed good agreement when estimated with the  $\mu\text{D}$  ( $|\text{MD}|=0.068\text{m}$ ;  $|\text{MPD}+\text{LOA}|=8.9\%$ ), and excellent agreement when estimated with the SkelR and SkelS methods ( $|\text{MD}|<0.010\text{m}$ ;  $|\text{MPD}+\text{LOA}|<2\%$ ). The  $\mu\text{D}$  method underestimated SL while both skeleton methods slightly overestimated SL. STV showed poor agreement when estimated with the  $\mu\text{D}$  and SkelS methods ( $|\text{MD}|<10.8\%$ ;  $|\text{MPD}+\text{LOA}|>52.0\%$ ) and moderate agreement when estimated with the SkelR method ( $|\text{MD}|=12.3\%$ ;  $|\text{MPD}+\text{LOA}|=17.8\%$ ) with values obtained with RF methods systematically larger than those obtained with the MRK method. Noticeably, SkelS showed the lowest absolute error ( $|\text{MD}|=8.85\%$ ) but resulted in poorer agreement due to a larger standard deviation. For all methods, SLV showed moderate agreement ( $|\text{MD}|<23.7\%$ ;  $|\text{MPD}+\text{LOA}|<37.6\%$ ), with values obtained with RF methods systematically larger than those obtained with the MRK method.

#### IV. DISCUSSION

The aim of this study was to provide an overview of emerging radar-based techniques for gait parameter estimation, the results of a pilot study in which we compared the accuracy of different radar-based QGA techniques, and a discussion to highlight areas requiring future research.

Depending on the available technology, gait variables associated with fall risk can range from very simple to complex. Most radar-based gait parameters estimation studies focused on estimating gait speed [55][56][61][64][101]. Perhaps, gait speed is the most common and simple outcome sensitive to pathology and can be considered as the final common expression of locomotor control [102], with higher risk for falls associated with slower self-selected walking speed. However, gait speed cannot reveal the underlying impairments and measurement of spatio-temporal and biomechanical parameters of gait are useful to augment diagnostic capabilities. The gait

pattern in older people at higher risk for falls is usually stiffer, less coordinated, and characterized by poorer postural control, shorter stride length and height, wider step width, and greater propensity of landing flatfoot.

After gait speed, step time is the spatio-temporal parameter that most radar-based studies tried to estimate. The results from this study and other studies show that excellent agreement in average step time recognition is achieved between RF and the Vicon systems [55], independently by the RF processing technique. To the best of our knowledge, few radar-based studies have attempted to validate step length estimation [55][61]. However, both estimated step length by multiplying step time by the average walking [61] or treadmill [64] speed. Both studies reported small estimation errors of about 2-3%. Instead, we proposed to estimate step length by directly calculating the distance between ankle markers when reconstructing the skeleton or integrating the approximated trunk velocity curve over a step when using the  $\mu\text{D}$ . When attempting to estimate spatial components of gait, we observed an underestimation of the average step length of about 13% when using the  $\mu\text{D}$  method. Using either of the RF skeleton methods significantly improved the estimation performance. Using SkelR, we obtained an overestimation of only 2% of step length. When using SkelS, estimation can be further improved to 1% of error. It should be taken into account that estimating spatiotemporal parameters using body point locations allow researchers to estimate a large number of spatio-temporal parameters such as step width, joint angles, and others.

Although the significant differences in the gait pattern of fallers and non-fallers, few quantitative studies have found measures of gait that can predict fall risk. A promising method to assess fall risk is the evaluation of gait stability parameters derived from biomechanics and dynamical systems theories [103]–[106]. Briefly, repetitive motor tasks, like walking, can be treated as a nonlinear dynamic system where variables have a cyclic behavior and recur iteratively with almost the same pattern during the temporal evolution of the task. This pseudo-periodic behavior can be exploited to quantify gait variability and nonlinear analysis. Alternatively, from a biomechanical point of view, dynamic stability can be defined as a measure of the distance between the center of mass and the base of support [107]–[109]. Features describing the variability and complexity of gait are the most sensible in assessing fall risk, as compared with standard quantitative measures of gait [110]–[113].

Accurate estimation of gait parameters at each gait cycle is fundamental to estimate gait dynamics. In radar research, this has been attempted in a few studies [55][56][61][64][114], but they did not systematically analyze gait variability. To the best of our knowledge, our group has been the first to evaluate the performance of RF sensors in estimating gait stability [62][63][70]. The pilot study in this work reveals that both micro-Doppler and skeleton estimation-based RF data analysis methods result in measures of variability that show poor to moderate agreement and overestimations of about 100% with respect to the Vicon system. To put this in perspective, it should be noted that previous studies that determined the concurrent

validity of gait variability measures obtained with inertial sensors [100][115]-[118] also showed that IMU-based measures have poor to moderate validity [119].

Although the small sample of young participants limited the power of the statistical tests and the generalization of our results to other populations at risk of falling, the pilot study was intended to provide an initial comparison of radar-based techniques for gait analysis and inform the reader about the current limitations of radar technology and the relationship between the specific radar hardware and accuracy. Even if this preliminary study did not provide real evidence that the system could properly identify signature gait characteristic of faller vs. non faller, the analysis of healthy young adults is the first step in developing a base for further studies on vulnerable populations. Future studies will focus on fall-prone older adults with diagnosed balance problems.

Next, we discuss the limitations of the specific commercially available radar used in the pilot study and aspects of current estimation techniques that adversely affected the accuracy of gait variability measures.

*Hardware Limitations:* The TI IWR2243 Cascade radar has the advantage of high angular resolution in the azimuth direction due to the ability of exploiting TDM to form a large 192 element virtual array – the more the number of virtual array elements, the finer the angular resolution. However, TDM requires multiple sweeps, which greatly increases the time required to form the virtual array (also known as a coherent processing interval, or CPI) and lowers the overall sample rate. In the pilot study, while the Vicon had a data rate of 100 Hz, the radar was operated at a data rate of just 10 Hz. Our results show that this rate is too low for adequate assessment of gait variability. Furthermore, it should be noted that the TI IWR2243 Cascade radar is able to achieve high angular resolution in just the azimuth direction: with only a few array elements in elevation, the elevation resolution is extremely poor. In depth, the 4 GHz bandwidth of the TI IWR2243 Cascade radar results in 3.75 cm depth resolution. Our results show that the accuracy of estimating skeletal key points is correlated with the radar's resolution; thus, the best accuracy was obtained in estimating position along the azimuth – the direction along which the radar had the highest resolution. Ideally, the optimal radar for gait parameter estimation would have both a low CPI, high bandwidth, and a large number of physical array elements in both the azimuth and elevation. Such a radar, however, results in such a large amount of data from the resulting 4D radar tensor that real-time processing on the edge becomes challenging. To resolve this dilemma in automotive applications, radar design companies have developed RF-system-on-a-chip (RF-SoC) that integrates the RF transceiver circuits with memory blocks, microprocessors and digital signal processing as a complex single-chip system. However, automotive RF-SoCs typically generate real-time point clouds, and do not provide developers access to the raw radar I/Q data required for computation of the micro-Doppler signature or accurate skeleton estimation. Moreover, there is a cost versus performance trade-off in commercially available

radar sensors – the larger the antenna arrays and greater the bandwidth, the higher the resolution and performance, but also the greater the cost. Thus, an open research question for gait parameter estimation is whether it would be better to use multiple, low-cost single-channel radars of high bandwidth or a single, more expensive multi-channel, high bandwidth radar.

*Processing Constraints:* The RF data representation from which gait parameter estimates are derived impacts both accuracy and the parameters that can be estimated. Established metrics for fall risk are based on accurate estimation of skeletal keypoints, which our study also shows offers improved estimation despite hardware limitations. An examination of the RF skeleton estimation literature shows that the more physical variables measured by the radar are used in the estimation process, the greater the accuracy of the resulting estimates. Thus, we have seen an improvement in accuracy when both range, angle, and Doppler are considered relative to range, angle, or micro-Doppler only. Here we should also make a distinction between methods that take as input the radar data tensor (range-frequency-angle vs. time) versus methods that directly use radar point clouds. While the use of point clouds may seem expedient given its ready availability from commercially available RF-SoCs, the point cloud is itself a derived data representation based on the constant false-alarm rate (CFAR) detection applied to the radar data tensor. Although more recently developed RF-SoCs provide not just  $(x, y, z)$  coordinates for each point but also a Doppler shift ( $f_D$ ) measurement, it should be noted that these measurements are provided every CPI, which is the duration that  $N$  pulses can be transmitted at a pulse repetition interval (PRI) for each pulse. In contrast, a micro-Doppler signature contains a Fast Fourier Transform (FFT)-based estimate of micro-Doppler frequency (radial velocity) at an interval of  $PRI/N_{fft}$ , where  $N_{fft}$  is the number of FFT points utilized. As such, the micro-Doppler represents a much richer source of kinematic information than that embodied by point clouds. Thus, an open area of research is how to best process the RF data tensor to maximally exploit the complete set of measurements by a radar system for gait parameter estimation – and how to accomplish this in real-time to minimize latency and maximize sample rate.

*DNN Design Considerations:* The most widely used DNNs are networks that were proposed for the applications of computer vision and speech processing. However, radar data is not inherently an image, nor does it possess the same frequency-dependent properties as speech signals [120]. Consequently, from a DNN design perspective as well the RF data representation utilized at the input of a DNN will have a great impact on the resulting performance [121] both in terms of accuracy and latency. For example, direct utilization of the complex I/Q radar data at the input of a CNN can reduce computation time, enabling real-time applications, but has greatly degraded performance relative to that of utilization of the micro-Doppler signature at the input. Recently, the inclusion of complex sinc filtering layers prior to the convolutional layers has been proposed to attain comparable performance with low latency [122]. Another disadvantage of



CNN-based skeleton estimation methods is that they do not consider the spatial correlation inherent to human movement. Although the CNN+LSTM model does incorporate sample-to-sample correlations, our pilot study examining results on simulated data is evidence that there remains a significant amount of estimation uncertainty due to network design and training. Finally, it should be noted that deep learning-based methods are very data greedy, and that not just the amount of data but also how the data was collected – under what scenarios, sensor positions, environment, and the mobility characteristics of the participants utilized – will impact model training and resulting estimation accuracy. Thus, there remains much opportunity for future research in DNN design that can contribute to improved radar-based gait parameter estimation accuracy.

*Environmental Factors:* In application of radar-based QGA technologies in home, signal processing and AI/ML algorithms must also take into consideration dynamic environmental factors, such as the separation of radar signatures from multiple people [123]-[125] and potential presence of obstacles or other sources of motion in the scene being illuminated by the radar, such as a fan or pet. Thus, while on the one hand researchers are developing more advanced signal processing and micro-Doppler decomposition [126]-[128] algorithms, on the other hand some researchers have proposed positioning the radar in hallways [56], where obstacles are not expected and motion is automatically constrained by the walls, or utilizing the radar in a cognizant fashion by potential users, such as the case would be if conducting an in-home TUG test. Dynamic environmental factors, including sensor positioning, will also impact the ability of DNNs to generalize across environments and thus must be accounted for during training and network design.

## V. CONCLUSION

This paper has provided an overview of emerging radar-based techniques for gait parameter estimation, especially with emphasis on those relevant to fall risk. A pilot study was conducted that compares the accuracy of gait parameters estimation from different radar data representations (i.e., micro-Doppler signature and skeletal point estimates) against an 8-camera, marker-based optical tracking system. The results of this study show that while there is excellent agreement between radar and optical tracking estimates of step time and step length, gait variability measures show poor to moderate agreement. The limitations of current radar-based technology that adversely affect the accuracy of radar-based gait variability measures – such as trade-offs between transceiver architecture, transmit waveform parameters, and cost, processing constraints, and DNN design considerations – are discussed. We conclude by pointing out areas for future research that can address current limitations and enable the realization of radar-based QGA as a promising emerging technology for continuous, non-intrusive fall risk assessment.

## CONFLICT OF INTEREST

The authors declare that they have no commercial or financial relationships that could be construed as a potential conflict of interest.

## AUTHOR CONTRIBUTION

S.Z. Gurbuz, M.M. Rahman, and D. Martelli contributed to the conception and design of the study, algorithm development, interpretation of results and manuscript writing. Z. Bassiri contributed to the data collection and curation. S.Z. Gurbuz and M.M. Rahman were primarily responsible for the radar-related sections of the paper, while D. Martelli focused on biomechanics, gait analysis and pilot study sections of the paper. Additionally, each author contributed their specialized expertise in their respective research domains to the overall interpretation, discussions and insights offered by the paper, as well as reviewing and editing the manuscript.

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