3-D Gait Abnormality Detection Employing Contactless IR-UWB Sensing Phenomenon

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Abstract—Gait disorder diagnosis and rehabilitation is one area where human perception and observation are highly integrated. Predominantly, gait evaluation comprises technological devices for gait analysis, such as dedicated force sensors, cameras, and wearable sensor-based solutions; however, they are limited by insufficient gait parameter recognition, postprocessing, installation costs, mobility, and skin irritation issues. Thus, the proposed study concentrates on the creation of a widely deployable, non-contact and noninvasive gait recognition method from impulse radio ultrawideband (IR-UWB) sensing phenomenon, where a standalone IR-UWB system can detect gait problems with less human intervention. A 3-D human motion model for gait identification from IR-UWB has been proposed with embracing spherical trigonometry and vector algebra to determine knee angles. Subsequently, normal and abnormal walking subjects were involved in this study. Abnormal gait subjects belong to the spastic gait category only. The prototype has been tested in both anechoic and multipath environments. The outcomes have been corroborated with a simultaneously deployed Kinect Xbox sensor and supported by a statistical graphical approach Bland and Altman (B&A) analysis.

Index Terms—3-D gait identification, Bland and Altman (B&A) plot, gait, impulse radio ultrawideband (IR-UWB), Kinect Xbox Sensor.

I. INTRODUCTION

Gait or human locomotion is a bipedal, sinuousid, forward propulsive movement of the human body where upper and lower limbs coordinate simultaneously. This is a complex translatory motion, including the brain, spinal cord, peripheral nerves, muscles, bones, and joints [1]. Physically, each and every bone of the human skeleton participates in the process, but empirically, the bones of the pelvis and lower limb are considered to realize this repetitive motion. There has been a growing interest to better characterize gait or detect abnormalities when people are unable to walk in a normal way, particularly among practitioners, physiotherapists, biomedical engineers, neurologists, and rehabilitation societies. Abnormalities occur because of injuries to the legs or feet, arthritis, infections in the soft tissue of the legs, broken bones in feet and legs, birth defects, infections in the inner ear, cerebral palsy, stroke, tendonitis, neuropathy, conversion disorder, or other psychological disorders and shin splints [2].

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Mokhtari et al. [12] prototyped a UWB model to identify gait signatures of different persons employing region-of-interest (ROI) approach. Furthermore, backscattered energies are measured from the ROI and used as features to categorize different persons using support vector machine (SVM), random forest (RF), logistic regression, \( k \)-nearest neighbor (\( k \)NN), and neural network (NN) models. Potluri et al. [13] measured the significant gait parameters using wearable plantar pressure and inertial sensors to investigate differences between normal and abnormal walking patterns identified by a long short-term memory (LSTM) model to predict the risk of fall. Similar research by Gao et al. [14] employed inertial sensors to obtain abnormal gait pattern step information, including hemiplegic, tiptoe, and cross-threshold gait. The step features were employed in a hybrid model of LSTM and convolutional neural network (CNN) to classify abnormal gait. Ren et al. [15] modeled a system to extract \( \mu \)-D features from UWB radar for gait stride identification employing short-time state-space method (STSSM). In addition, Orović et al. [16] proposed a human gait classification method that relies on motion signatures from arm and leg movements obtained through a continuous-wave (CW) radar signal. The widely used WSs are force sensors (FSs), accelerometers, gyroscope, extensometers, goniometers, electromyography (EMG), active markers, and so on placed at the hips, feet, and so on to assess gait characteristic [17]. Bruening and Ridge [19] reviewed existing algorithms related to gait events, velocity, and acceleration of foot/heel strike, toe off. The data are collected through foot and sacrum markers initially to make ground-truth information and the simulation repeated to obtain said gait parameters. The work claims that the existing study carried out by Ghousayni et al. [18] to measure sagittal velocity is reliable for clinical gait application, while a single algorithm is not sufficient to measure all gait events [19]. Greene et al. [20] developed an adaptive algorithm to measure initial contact (IC) and terminal contact (TC) timing of the foot via gyroscopes. In addition, it calculates angular velocity, stride length, swing time, stance time, and step times from human gait. The study includes force measurement plates and an optical motion capture system to compare the obtained results with the proposed algorithm. Bugané et al. [21] prototyped an accelerometer-based gait characterization model to measure single and double support interval from gait event. Also, it determines spatial and temporal parameters, such as stride length and duration, cadence, and speed. Popular gait analysis methods, stereophotogrammetry and dynamometry, are employed for validation. Industry is working in parallel to academic research toward the creation of robust and efficient gait analysis tools. CONTEMPLAS produced a professional motion analysis software TEMPLO for clinical gait analysis [22]. This is a hybrid approach for gait measurement solution that uses both NWS and WS systems for diagnosis. Tekscan makes pressure mapping, force measurement, and tactile sensors for clinical gait assessment [23]. They primarily focus on force platforms but use additional instruments, such as video scan and EMG analysis to construct a hybrid tool for gait characterization.

The NWSs (such as force platform, pressure plate, and GRF sensor) for gait analysis are parameter-specific, e.g., a force platform only delivers step duration and step length that are not sufficient to detect abnormal gait. The clinical setup needs several devices to take decisions on gait patterns, which increases time, space, and cost complexity. Subsequently, cameras, such as laser range scanners, infrared sensor camera, and time-of-flight (ToF) camera, are also a type of NWSs for gait characterization but consume huge effort to differentiate between foreground (patient or object) and background (stationary backdrop) before any calculation of significant biomechanical parameters. The WSs, such as active markers, FSs, and magnetometers, measure gait parameters more precisely compared to NWSs as they measure biomechanical parameters of gait trajectory in 3-D, which describes a walk that is better than the parameters obtained from NWS. The patients do feel uncomfortable when several markers are placed on the body during examination. The field needs alteration methods preferably NWS without camera integration, which would be adequate to measure human gait in noncontact and noninvasive manner providing precise decisions in gait characterization. One potential technology is UWB Doppler radar, which had been employed in continuous mode and operated in frequency modulation. However, the CW UWB radar does not provide propagation delay information for each pulse to measure frequency shift, which restricts it only to calculate the rate of change of range. A handful of UWB Doppler-based gait identification works are accomplished using impulse radio but focus on spectrogram and \( \mu \)-D, which can provide the frequency of lower movement and walking speed, respectively. However, the prospects of IR-UWB have not been fully explored, which could provide 3-D gait quantification and have advantages, such as mobility, ease of installation, remote access, and cost efficiency over typical NWS and WS.

A. Contribution

This study develops an IR-UWB pulsed Doppler radar-based prototype for quantitative human gait analysis demonstrating a noncontact and nonintrusive 3-D human motion model. The initial model previously proposed in [24] is now augmented and improved to determine further significant gait parameters. The contributions of this work are given in the following.

1) The radar pulse energy flow has been transformed into a wave vector using spherical trigonometry and vector algebra to capture the backscattered pulses from human motion in 3-D. Here, anatomical planes, such as frontal, sagittal, and transverse plane, are elucidated by motion width, range, and height of movement to represent the unit vectors.

2) The study has created a mathematical model to express the right and left knee angles as cosine angles that can be computed by the product of the Euclidean magnitudes of the two vectors formed, through motion width, range, and height.

3) The real data collection process has been extended involving a greater number of human participants (24 hitherto) following ethical approval guidance. The developed prototype has been tested in both an anechoic chamber and multipath environment employing real data.
for normal and abnormal walking to distinguish walking patterns.

4) Simultaneously, the Kinect Xbox One sensor has been chosen to corroborate the obtained results from the proposed IR-UWB prototype, where the Kinect’s skeleton joints have been symbolized as vectors and projected as one vector onto another to derive the right and left knee angles.

5) The Bland and Altman (B&A) plot has been considered to compare the twofold experimental results obtained from both IR-UWB and Kinect to establish an agreement between them. The proposed IR-UWB is found to be superior or equivalent to Kinect in both the environments from this research study.

The remaining sections of this article are organized as follows. A description of the laboratory setup, UWB data acquisition, proposed methodology, Kinect sensor, and data interpretation procedure, and B&A analysis are discussed in Section II. Experimental results have been demonstrated in Section III. Section IV concludes this article and provides future research directions.

II. Methods

The knee angle has a compelling effect on gait and is the angle between the straight line joining the lateral malleolus fibula head and a straight line joining the lateral femoral epicondyle great trochanter. The knee angle is a pivotal parameter for gait biomechanics and it shows significant variation during abnormal walking. The participants involved in this study have the common problem of spasticity for the muscles around the knee during leg swing but also display a lower level of spasticity around the ankle and hip joints. Thus, the proposed prototype described here focuses on the knee angle (right and left) calculation of human gait during flexion and the extension of the leg muscles. A flowchart of this work is shown in Fig. 1. The work is divided into seven parts: laboratory setup, participant recruitment and their subjective data collection, data processing, the proposed spherical trigonometric approach and its vectorization for determining knee angles, Kinect Xbox sensor calibration and its vectorization for determining knee angles, and the result comparison through a B&A plot to justify the potentiality of the proposed work. Each of these aforementioned tasks has been detailed in the following.

A. Laboratory Setup

A time-domain PulsON P410 monostatic radar module (P410 MRM) has been used to collect all the physiological UWB sensing phenomena reported here and published in [24]–[28], which is shown in Fig. 2(a). The device is a monostatic pulsed Doppler radio transceiver, which utilizes TW-ToF omnidirectional range measurement techniques as a hybrid ranging radio and a radar sensor device for nonintrusive human gait measurement. The device has been configured before data collection, and the same configuration has been maintained for both of the chosen (tested) environments. The PulsON P410 module generates Gaussian pulses and transmits the first-order derivative of the Gaussian pulse providing high power efficiency by delivering extremely low power spectral density (PSD) to mitigate the influence of surrounding multipath environments. In addition, the nanosecond duration Gaussian pulses have low duty cycle resulting in a high pulse repetition rate (PRR) of 10 MHz enabling improved detection of human movement of transmitting the radio frequency (RF) range of a lower frequency limit 3.1 GHz to an upper frequency limit 5.3 GHz, with the center frequency at 4.3 GHz, and a bandwidth of 2.2 GHz (where the fractional bandwidth of P410 device is 51.16%) addresses to FCC restrictions [29] for power. Transmission power to the antenna port is specified as −12.64 dBm for safe RF transmission [29]. The scan time window for this experiment is 87.84 ns long, but the first 5 ns of the radar signal is neglected in order to negate noise and direct path interference between transmitter and receiver antenna, and thus, the signal during the first 5 ns is filtered from the subsequent analysis. The scan interval is set to 25 000 μs. The received reflected pulsed signals are sampled in 61-ps steps, which results in a sampling frequency fs = 16.39 GHz, with a pulse repetition interval (PRI) of approximately 100 ns.

B. Data Acquisition

Twenty-four human participants were involved in this data collection process. Initially, gender and anatomical information (height and length of the limbs) have been recorded for each individual, as shown in Fig. 2(d). The recorded
information from all 24 subjects is tabulated in Table I, where length of leg, length of thigh, and length of shank have been denoted by LoL, LoT, and line of sight (LOS), respectively. Full ethical approval (Reference Number: Eng. 01Dec2017) was gained from London South Bank University, where the research code of practice and ethical guidelines are governed by the university ethics panel (UEP). All procedures performed in this study were in accordance with the ethical standards of the institutional and/or national research committee and the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Both anechoic chamber and multipath/normal (laboratory) environments have been used for the data collection. These two environments are shown in Fig. 2(b) and (c).

### C. Azimuth and Elevation Angles

To assist in the differentiation of separate body areas, azimuth and elevation angles are considered. This is further explained in Section III. Fig. 3(a) shows the elevation and azimuth angle at a particular time, where \( \Delta OAB \), \( \Delta OAB' \), \( \Delta OCB \), and \( \Delta OCB' \) are drawn from the received pulsed radar signal. Here, \( O \) is considered as the radar receiver, which is fixed at a point of height \( OP \) from the ground. Therefore, \( BC \) and \( CB' \) represent the height of a moving object from the radar LOS \( OA \). The moving body section is elevated from the radar LOS at an angle \( \theta \) and below the LOS at an angle \( \theta' \). Here, \( \Delta OAB \cong \Delta OAB' \) and \( \Delta OCB \cong \Delta OCB' \), and therefore, the height \( BC \) and \( CB' \) can be determined from the trigonometric relationships. Only the calculation of \( BC \) from \( \Delta OAB \) is explained. Let the angle between \( BC \) and \( OB \) be \( \alpha \). The traveled distances are \( OA \), \( OB \), and \( OB' \) in propagation delays \( t_1 \) and \( t_2 \) by the pulses, where \( t_1 > t_2 \) and \( t_1 > t_2' \) and \( OA > OB \) and \( OA > OB' \). Therefore, the change of distance is \( (OA - OB) = \Delta d \), the change of time is \( (t_1 - t_2) = \Delta t \), and the speed of light or pulse is \( c \). Therefore, pulse that can travel the distance in \( \Delta t \) is \( BC = \Delta t \times c \). From the trigonometric ratio in right triangle \( \Delta OCB \)

\[
\cos \alpha = \frac{BC}{OB} \Rightarrow BC = OB \times \cos \alpha
\]

\[
\Rightarrow \alpha = \cos^{-1}\left(\frac{\Delta t \times c}{OB}\right)
\]

Therefore, if the height of a moving object at a particular time is \( h \), then

\[
h = OB \times \cos \alpha.
\]

This calculation has the same outcome when \( t_1 < t_2 \) and \( t_1 < t_2' \) and \( OA < OB \) and \( OA < OB' \).

Fig. 3(a) shows the calculation for the azimuth angle to determine the position or orientation of moving limbs toward the radar. The spherical system measures the azimuth angle in a counterclockwise direction from the exact north of the receiver end denoted by \( \phi \). Let the moving limb deviate at an angle \( \phi \), where the traveled distances are \( XY \) and \( XW \) in propagation delay \( t_1 \) and \( t_2 \). Thus, the change of distance is \( (XY - XW) = YZ \) at the time interval \( (t_1 - t_2) = \Delta t \). The object is deviated from the exact north of the receiver. Now, \( YZ \) is approximately equivalent to the arc \( YW \) created by the object at angle \( \phi \). Therefore, \( \phi \) is calculated from the radian measure, and equivalent degree conversion is

\[
\phi = \frac{YZ \times 360^\circ}{XY \times 2 \times \pi}.
\]

Therefore, the position or the coordinate of a pulse hitting a human body would be found by considering range, elevation, and azimuth calculations. Let a pulse that has backscattered from human body be its arc, range, and height that are \( a, r \), and \( h \), respectively. Once the position of backscattered pulses from a human body has been identified, the points have been considered as vector (e.g., \( \hat{i} + r \hat{j} + Rh \)), where \( i, j, \) and \( k \) are unit vectors of three planes) in a 3-D space to determine

| No | Gender | Height (m) | LoL (m) | LoT (m) | LoS (m) |
|----|--------|------------|---------|---------|---------|
| 1  | Female | 1.58       | 0.85    | 0.43    | 0.42    |
| 2  | Female | 1.54       | 0.83    | 0.42    | 0.41    |
| 3  | Female | 1.64       | 0.88    | 0.45    | 0.43    |
| 4  | Female | 1.73       | 0.93    | 0.47    | 0.46    |
| 5  | Female | 1.62       | 0.87    | 0.44    | 0.43    |
| 6  | Female | 1.71       | 0.91    | 0.46    | 0.45    |
| 7  | Female | 1.69       | 0.91    | 0.46    | 0.44    |
| 8  | Male   | 1.87       | 0.88    | 0.45    | 0.43    |
| 9  | Male   | 1.76       | 0.91    | 0.46    | 0.45    |
| 10 | Male   | 1.71       | 0.88    | 0.45    | 0.43    |
| 11 | Male   | 1.72       | 0.88    | 0.45    | 0.43    |
| 12 | Male   | 1.64       | 0.84    | 0.42    | 0.42    |
| 13 | Male   | 1.78       | 0.92    | 0.47    | 0.45    |
| 14 | Male   | 1.79       | 0.92    | 0.46    | 0.46    |
| 15 | Male   | 1.78       | 0.92    | 0.47    | 0.45    |
| 16 | Male   | 1.78       | 1.00    | 0.52    | 0.48    |
| 17 | Male   | 1.75       | 1.02    | 0.52    | 0.50    |
| 18 | Male   | 1.72       | 1.00    | 0.51    | 0.49    |
| 19 | Female | 1.55       | 0.95    | 0.50    | 0.48    |
| 20 | Female | 1.53       | 0.94    | 0.50    | 0.44    |
| 21 | Male   | 1.76       | 1.03    | 0.54    | 0.49    |
| 22 | Male   | 1.78       | 1.01    | 0.53    | 0.48    |
| 23 | Female | 1.65       | 0.97    | 0.50    | 0.47    |
| 24 | Female | 1.38       | 0.95    | 0.49    | 0.46    |
the gait parameters. The subscripts of $a$, $r$, and $h$ have been used throughout this article to denote arc, range, and height of a backscattered pulse. The properties of vector algebra have been applied to measure the step length, hip angle, and knee joint angles for each participant using the \textit{a priori} knowledge of human body sections and detailed in the following.

**D. Knee Angle Calculation From IR-UWB Model**

The human knee joint has two sections: thigh and shank. Thus, human gait creates an angle between these two muscles during the walking process. The angle increases during muscle extension (i.e., the straightening of the legs) and decreases during muscle flexion (i.e., articulation of legs). The change in knee joint angle is significant to characterize human gait. Fig. 3(b) shows a human walking posture where two points $L_T$, $L_S \in \mathbb{R}^3$ Euclidean space at time $t$ have been assumed on thigh and shank of left leg, respectively. The dot product of these two points provides the acute angle $\gamma_L$ between them, whereas the measurement of the obtuse angle ($\beta_L$) is anatomically more significant. The detailed calculations of $\gamma$ and $\beta$ have been included in (4) and (5):

$$
\overrightarrow{L_T \cdot L_S} = |L_T||L_S| \cos \gamma
$$

$$
\Rightarrow \cos \gamma_L = \frac{\overrightarrow{L_T \cdot L_S}}{|L_T||L_S|}
$$

$$
\Rightarrow \cos \gamma_L = \frac{a_1 i + r_1 j + h_1 k \cdot (a_2 i + r_2 j + h_2 k)}{|a_1 i + r_1 j + h_1 k||a_2 i + r_2 j + h_2 k|}
$$

$$
\Rightarrow \cos \gamma_L = \frac{a_2 a_1 + r_2 r_1 + h_2 h_1}{\sqrt{a_1^2 + r_1^2 + h_1^2} \sqrt{a_2^2 + r_2^2 + h_2^2}}
$$

$$
\Rightarrow \gamma_L = \cos^{-1} \left( \frac{a_2 a_1 + r_2 r_1 + h_2 h_1}{\sqrt{a_1^2 + r_1^2 + h_1^2} \sqrt{a_2^2 + r_2^2 + h_2^2}} \right).
$$

Therefore, the obtuse knee angle ($\beta_L$) for the left leg

$$
\beta_L = 180^\circ - \gamma_L.
$$

Similarly, the acute knee angle $\gamma_R$ between $R_T$ and $R_S$ for right leg has been determined in the following equation:

$$
\gamma_R = \cos^{-1} \left( \frac{a_3 a_4 + r_3 r_4 + h_3 h_4}{\sqrt{a_3^2 + r_3^2 + h_3^2} \sqrt{a_4^2 + r_4^2 + h_4^2}} \right).
$$

Therefore, the obtuse knee angle for right leg has been included in the following equation:

$$
\beta_R = 180^\circ - \gamma_R.
$$

**E. Calibration of Kinect Xbox One**

The results obtained from the proposed model have been corroborated by measuring the knee angles with the Microsoft Kinect Xbox One. It includes a 3-D image and voice sensor and employs a ToF technology to deliver high-resolution, low-latency, light-independent 3-D image sensing. The Kinect sensor tracks the 3-D human skeleton using color and depth sensors [30]. It has the potential as a low cost, accurate gait motion analysis tool, which has a good correlation with VICON Nexus motion capture system for hip, knee, and stride timing measurements. Furthermore, the study shows that error is low and correlation high for stride and knee angle measurement compared to hip angular measurements carried out by Kinect and VICON sensor [5]. The proposed work aims to characterize human gait in a nonintrusive manner, so the device has been calibrated to obtain color and skeleton only from the video. Frames per second (FPS) has been fixed at 30 for color and depth sensor for video acquisition. The camera has a field of view of 70° horizontal and 60° vertical. The camera sensor operates at a range from 0.8 to 4.2 m in one room only (unlike the model developed which has through wall capability) from the device. It tracks the skeleton from a moving body posture (as shown in Fig. 4) and provides the 3-D joint coordinates. The Kinect sensor delivers 20 skeletal data (3-D joint coordinates) at the standing condition from the body posture. This skeletonization process is similar to the proposed prototype permitting the validation of the work via the Kinect sensor. Fig. 4(b) shows the 20 joints (white markers) from a human body where the validation process has used only six joints from the lower limb of a human body, such as the hip left ($\overrightarrow{HL}$), knee left ($\overrightarrow{KL}$), ankle left ($\overrightarrow{AL}$), hip right ($\overrightarrow{HR}$), knee right ($\overrightarrow{KR}$), and ankle right ($\overrightarrow{AR}$). Then, the vector algebra has been employed on these joints to validate the proposed outcomes, such as step size, number of steps, speed, hip angle, and knee angles (for both left and right leg). Let be the vectors $H \overrightarrow{L}$, $K \overrightarrow{L}$, $A \overrightarrow{L}$, $H \overrightarrow{R}$, $K \overrightarrow{R}$, $A \overrightarrow{R}$ $\in \mathbb{R}^n$ in the Euclidean n-space. The component form of these vectors has been denoted as $H \overrightarrow{L} = a_i \hat{i} + r_j \hat{j} + h_k \hat{k}$, $K \overrightarrow{L} = a_\delta \hat{i} + r_\gamma \hat{j} + h_\delta \hat{k}$, $A \overrightarrow{L} = a_\alpha \hat{i} + r_\beta \hat{j} + h_\alpha \hat{k}$, $H \overrightarrow{R} = a_\alpha \hat{i} + r_\beta \hat{j} + h_\gamma \hat{k}$, $K \overrightarrow{R} = a_\delta \hat{i} + r_\gamma \hat{j} + h_\delta \hat{k}$, and $A \overrightarrow{R} = a_\alpha \hat{i} + r_\beta \hat{j} + h_\delta \hat{k}$ where subscripts with $a$, $r$, and $h$ represent the distance from $i$, $j$, and $k$. 

![Fig. 4. Sample video frame of human gait tracked through Kinect color and depth sensor. (a) Frame from color sensor. (b) Frame from depth sensor.](image-url)
and $\hat{k}$ planes, respectively. These vectors have been further used to determine parameters for gait characterization in the following.

### F. Knee Angle Calculation From Kinect

The knee angles (left and right) have been measured in a similar way to the hip joint calculation using the vector dot products. The knee and ankle joints [shown in Fig. 4(b)] from skeletal data of both legs have been used to calculate the knee angles of human gait. In the case of the left leg, the connecting skeletal data of both legs have been used to calculate the knee products. The knee and ankle joints [shown in Fig. 4(b)] from F . Knee Angle Calculation From Kinect

The acute angle has been denoted by $\gamma'_{\text{L}}$ and detailed in the following equation:

$$\gamma'_{\text{L}} = \cos^{-1} \left( \frac{a_{56}a_{67} + r_{56}r_{67} + h_{56}h_{67}}{\sqrt{a_{56}^2 + r_{56}^2 + h_{56}^2} \sqrt{a_{67}^2 + r_{67}^2 + h_{67}^2}} \right).$$

(8)

Therefore, the inner knee angle or obtuse knee angle for the left leg

$$\beta'_{\text{L}} = 180^\circ - \gamma'_{\text{L}}.$$  

(9)

Similarly, the acute knee angle $\gamma''_{\text{R}}$ between $\vec{R}_{\text{T}}$ and $\vec{R}_{\text{S}}$ for right leg has been determined in the following equation:

$$\gamma''_{\text{R}} = \cos^{-1} \left( \frac{a_{89}a_{910} + r_{89}r_{910} + h_{89}h_{910}}{\sqrt{a_{89}^2 + r_{89}^2 + h_{89}^2} \sqrt{a_{910}^2 + r_{910}^2 + h_{910}^2}} \right).$$

(10)

Therefore, the obtuse angle or inner knee angle for right leg would be

$$\beta''_{\text{R}} = 180^\circ - \gamma''_{\text{R}}.$$  

(11)

### G. B&A Plot Analysis

The proposed IR-UWB prototype and Kinect have been used here to measure the same gait parameter, i.e., knee angle with differences found. Subsequently, the outcomes have been compared using the B&A plot analysis [31], [32] based on the quantification of the agreement between two quantitative measurements by studying the mean difference and constructing limits of agreement to assess the comparability between the methods. The statistical limits are calculated using the mean, standard deviation of the differences between the two measurements, and a hypothetical graphical approach to indicate the agreement. The knee angle of participants has been measured through both the proposed and Kinect systems. Let the measured knee angles from the proposed and Kinect system be $k_p$ and $k_s$, respectively, and the mean of knee angle is $mk$, the differences between paired knee angle are $d_k$, and the standard deviation of the differences obtained for knee angle is $sk$. The graphical approach is employed to observe the assumptions of normality of differences and other characteristics where the $x$-axis represents the average of measurements and the $y$-axis shows the difference between the two measurements. The two systems would agree when most of the consequences lie within $d_k \pm 1.96 sk$ for the measurement of knee angle. More precisely, 95% of differences must lie within $d_k \pm 1.96 sk$ for measuring the knee angle according to the B&A analysis. Thus, the null hypothesis states here that there is no significant difference between populations (measurements) when using the proposed gait identification model and Kinect for determining knee angles of participants where probability value $p < 0.05$ indicates acceptance of null hypothesis and correctness of assumption.

### III. Result Analysis

As explained, the experiment has been conducted in two environments: anechoic and multipath to investigate robustness, cost effectiveness, and suitability. In addition to this, the preciseness and acceptance of the work for gait characterization has been supported through the B&A plot analysis in each environment. The results and B&A plot analysis are presented in the following.

#### A. Result Analysis From Anechoic Chamber

The comparative analysis of the obtained results from the proposed prototype and Kinect sensor is demonstrated in this section. The processing of IR-UWB data and interpretation has been discussed in Section II-C, which explains the positions of backscattered pulses from a human body and defines motion through the IR-UWB. Fig. 5 shows one of the 20 normal walking patterns through the IR-UWB response in 3-D over an observation period, where Fig. 5(a) and (b) shows the front and side views of walking motion captured through the proposed model.

The $x$-, $y$-, and $z$-axes signify gait motion width, distance from radar, and height of movement, respectively. The motion appears like the letter “W,” showing the symmetry of the human body with three areas labeled $P_1$, $P_2$, and $P_3$. Here, the area $P_1$ reflects the hip joint of that person, and $P_1$ to $P_2$ and $P_2$ to $P_3$ denote the change of position of human body due to gait motion when one leg is lifted off of the ground and another leg is contacted the ground to push forward the body during walking. The person walked back and forth in front of the radar (within the 3-m test bed) during the observation times creating the distinct areas ($P_1$, $P_2$, and $P_3$) in 3-D. Also, the distance between the bottom of $P_2$ and $P_3$ areas represents...
that allows UWB radar to capture motion. The extension of transmission of higher energy by the biomechanical process muscles move faster than the other body sections implying the muscle’s (i.e., arm and legs) motion over time. The skeletal which includes the flexion and extension of the skeletal chamber.

Fig. 6 shows the 3-D structure resembling the letter “W,” which includes the flexion and extension of the skeletal muscle’s (i.e., arm and legs) motion over time. The skeletal muscles move faster than the other body sections implying the transmission of higher energy by the biomechanical process that allows UWB radar to capture motion. The extension of lower limbs (left and right) creates a separate motion area, whereas the flexion (right and leg) of the lower limb and upper limbs creates a linear region from the shoulders that explains human motion. The person shown in Fig. 6(a) and (b) has an actual height of 1.55 m, whereas the estimated height of the shape is 1.35 m. This is because the model has captured all movements by UWB up to the shoulder height from the ground level. The leg length of that participant 0.95 m and knee height 0.45 m from the ground level have been used to separate each lower limb section to determine the left and right knee angles. Fig. 6(c) and (d) shows the estimation of knee angles from the proposed study and Kinect, respectively, using the method of (4), (6), (8), and (10). The x-axis denotes the single gait cycle (in percentage) of a person by considering two consecutive steps and the process has been repeated for 30 s and then plotted in the y- and z-axes representing the knee angles during the observation time. The outcomes have been detailed here for 30 s for each participant. This participant has walked at a speed of 1.33 m/s (obtained from the Doppler effect), and the knee angles obtained from the proposed prototype vary between approximately 120° and 178°, whereas the angles obtained from the Kinect results vary between approximately 122° and 175°. The troughs here represent the angles during flexion, and the crest signifies the angles at the time of leg extension.

Fig. 7 shows one of the abnormal walking patterns through the IR-UWB response in 3-D over the same observation period, where Fig. 7(a) and (b) shows the front and side views of the walking motion captured through the proposed model. The x-, y-, and z-axes signify gait motion width, distance from the radar, and height of movement, respectively. The motion again appears like the letter “W” and shows the symmetry of the human body, and again, there are three areas labeled as P1, P2, and P3. However, Fig. 7 has differences from Fig. 5. Here, the abnormality creates two extra regions for the abnormal leg movement (spasticity). Similarly, the area P1 reflects the hip joint of that person, and P1 to P2 and P1 to P3 denote the change of position of human body due to gait motion when one leg is lifted off of the ground and another leg is contacted to the ground to push the body forward during walking. As before, the person walked back and forth in front of radar (within 3 m of test bed) during observation time that creates separate areas (P1, P2, and P3) in 3-D for change of position. Overall, the person’s movement is effected by their condition in particular one leg which is affected by their spasticity, and hence both legs create two separate areas in P2 and P3. This shows that the person needs to stretch and drag one leg more than a regular walker and this motion reflected in the proposed IR-UWB model outcomes. Also, the distance between the bottom of P2 and P3 areas represents step base width, which is also different from the normal walk. In addition, two areas detected above leg height are the hand movements (both right and left legs).

Fig. 8 shows the gait details of that person through IR-UWB and Kinect. Fig. 8(b) shows the motion of the said participant and stiffness of the left leg muscle forces the person to stretch the leg more during walking. Fig. 8(a) shows that the leg
deviates more from the center of the body during walking, resulting in the unusual knee angle variation between 135° and 163° determined from the proposed prototype. The knee angles obtained from Kinect are changes between 139° and 171° approximately.

B. B&A Plot: Results Obtained in Anechoic Chamber

The results obtained from the proposed model and Kinect system have been corroborated through a B&A plot analysis. The theoretical details of B&A plot have been demonstrated in Section II-G to support the measurement of knee angle utilizing the proposed model. Fig. 9 shows that B&A plots have been constructed on knee angle measurements from the proposed prototype and Kinect sensor, where Fig. 9(a) shows the B&A plots of knee angle measurements taken from 20 normal gait persons using the proposed prototype and Kinect, respectively, and Fig. 9(b) shows the B&A plots of knee angle measurements taken for four abnormal gait persons from the proposed prototype and Kinect system. The x- and y-axes represent the mean of the two measurements and difference between two paired measurements, respectively. Both the developed model and Kinect methods imply some degree of error, but the B&A plot indicates the relationship and agreement between these two methods for gait analysis. Fig. 9(a) shows that the bias or mean of difference is −0.847, signifying that the second method here Kinect always produces 0.847° units more than the proposed model and 95% differences are within \( d_k \pm 1.96 s_k \) while measuring knee angles. In addition, Fig. 9(b) shows the bias at −2.242 when measuring abnormal gait patterns, indicating that Kinect always delivers 2.242° units more than the designed prototype for the measurement of knee angles and 95% differences are within \( d_k \pm 1.96 s_k \) in this context. Thus, both cases suggest that the null hypothesis (there is no significant difference between the proposed prototype and Kinect system’s magnitude while measuring knee angles) is true and the developed model would be an alternative gait analysis method for consideration.

C. Result Analysis From Multipath Environment

Fig. 10(a) and (b) shows the 3-D motion captured from a person’s gait by the proposed prototype and Kinect, respectively, in the multipath environment (laboratory and corridor environment). Fig. 10(c) and (d) shows the obtained knee angles from the proposed and Kinect systems, respectively. The x-axis of Fig. 10(c) and (d) indicates the fractions of gait cycles covered by the knee angles during the observation time where each gait cycle contains two consecutive steps (stance \( \approx 60\% \) and swing \( \approx 40\% \) phase) with respect to the reference leg (left leg in this case) involved in the walking. The knee angle increases nearly at the time, while the reference leg is in the swing phase and decreasing in the stance phase, which is shown in Fig. 10(c) and (d). The variation of knee angles has been captured in the same way from the proposed prototype and Kinect system [in Fig. 10(c) and (d)]. The knee angle varies between 115° and 163° and between 122° and 163° while using the proposed prototype and Kinect system, respectively.

D. B&A Plot: Results Obtained in Multipath Environment

Here, the measurements taken in the multipath environment (laboratory environment) have been supported through
the B&A plot analysis the same as for anechoic chamber experiment. Fig. 11 shows the B&A plots constructed on knee angle measurements from the developed prototype and Kinect sensor, where Fig. 11(b) shows the B&A plots of knee angle measurements taken for 20 “normal” gait persons from the designed framework and Kinect with Fig. 11(a) demonstrating the B&A plots of the knee angle measurements taken for four abnormal gait persons via the developed system and Kinect in the normal or multipath environment. The $x$- and $y$-axes represent the mean of two knee angle measurements and the differences between their paired measurements, respectively. Fig. 11(b) shows that the bias or mean of difference is $-0.902$, which signifies that Kinect always produces $0.902$ degree units more than the proposed work to determine knee angles of normal gait persons where $p$ value is $1.0406 \times 10^{-6}$ (i.e., $p < 0.05$). In addition, Fig. 11(a) shows the bias at $-2.514$ when measuring knee angles of abnormal gait persons, indicating that Kinect always delivers $2.514$ degree units more than the constructed framework for the measurement of the knee angles, where $p = 0.0017$ (i.e., $p < 0.05$). Thus, the null hypothesis has been found to be true in both cases (normal and abnormal gait) in normal environment, $95\%$ differences are within $d_k \pm 1.96 \cdot s_k$, and there is no significant difference between the proposed framework and Kinect system’s magnitude while measuring knee angles in normal environment. This shows that the system has potential suitability for NWS gait analysis.

IV. CONCLUSION AND DISCUSSION

In this work, for the first time, a proposed 3-D model of human motion has been generated from noncontact, camera-free, IR-UWB sensing by employing trigonometry and vector algebra where subjective knowledge enabled the study to further characterize human gait. The scope of the current work considered identification of the knee angles only. The implementation execution time is proportional to the square of the scan number (or number of received pulses). Thus, the study requires quadratic time in real scenario, which costs $O(n^2)$ running time. Subsequently, a greater number of participants, including those with conditions, such as propulsive, waddling, and steppage, will be considered for future experiments. The Kinect sensor has been employed as a reference system used to evaluate the performance of the proposed model. The experiment has been conducted in both an anechoic chamber and “normal” environment where the proposed prototype and Kinect sensor have an accuracy of approximately 9 and 18 mm [33], respectively. Furthermore, Kinect suffers from the self-occlusion problem where one-half of the body is occluded by the other each time the participant turns around at the end of test bed. This problem only occurs at the $0^\circ$ azimuth beam angle in the IR-UWB model, whereas Kinect results are biased in $0^\circ$, $30^\circ$, and $60^\circ$ affecting the Kinect sensor. It has also been reported that the Kinect shows an error greater than $5^\circ$ in clinical settings for knee angle measurements [5]. Here, it has been found that the Kinect delivers $0.047^\circ$ (normal walks) and $2.242^\circ$ (abnormal walks) more in the anechoic environment, whereas $0.902^\circ$ (normal walks) and $2.514^\circ$ (abnormal walks) more in the real environment for the knee angle computation than the proposed work, which explored through the B&A analysis. The difference between the results obtained from the two devices occurs because of the self-occlusion problem and the number of joints detected. The Kinect is more biased in terms of self-occlusion. Also, Kinect only considers points over joints whether the problems may belong to somewhere between the joints, Kinect fails to represent this, whereas the proposed IR-UWB creates a rendered geometric pattern and detects more points all over the body, which is capable of detecting abnormalities more precisely. Hence, the obtained experimental result demonstrates the new system’s obvious potential, producing equivalent or better results than the Kinect sensor. The proposed model is a cutting-edge solution to address gait disability and monitoring by a noncontact IR-UWB technology as a plug-and-play option, e.g., field zones, local home systems, or care homes. Furthermore, this study will now be extended by employing supervised machine learning (SML) techniques to automatically recognize changes and identify human walking disorders, which involves dedicated sports laboratory conditions to perform gold standard test comparisons and realize SML algorithms to identify abnormality in gait automatically. This would provide a cutting-edge game changing and widely deployable solution in health and medical perspective to assist in clinical and pathological gait diagnosis.

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