Gait Analysis of Healthy and Parkinson's Disease Patients in Elderly Population Using FMCW Radar

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***Abstract*—Parkinson's Disease (PD) is a prevalent neurological disorder among elderly individuals, resulting in reduced gait control. Technological advancements have brought us many PD sensors based on gait analysis. Amongst these solutions, Radio Frequency (RF) sensors such as, Frequency Modulated Continuous Wave (FMCW) radars have been increasingly used due to their non-invasive nature and ability to operate across different lighting conditions. This study aims to assess the possibility of using FMCW radar-extracted gait parameters for PD detection. Four gait parameters were extracted using radar and reference Inertial Measurement Unit (IMU) sensors from twenty elderly participants including ten control and ten PD patients. The results suggest that FMCW radar can effectively measure step time, step length, step speed, and cadence with Mean Absolute Percentage Error (MAPE) of 8.8%, 10.17%, 9.01%, and 2.82%, respectively. Based on these parameters, gait asymmetry was also measured. The difference between the control group and the PD group in terms of the aforementioned parameters is used to verify the effectiveness of using radar for PD screening.**

Keywords*—*gait analysis, elderly care, Parkinson's disease, FMCW radar.

I. INTRODUCTION

The rise in life expectancy of the first world countries [1] has given rise to detective and preventive healthcare research. Particularly, in-home remote health sensing can be a useful early screening tool for several diseases. Remote healthcare sensing empowered by Artificial Intelligence (AI) has enabled several personalized healthcare solutions for the high risk (aging) population [2] [3].

Parkinson's disease (PD) is a frequently occurring neurodegenerative disorder in elderly individuals which is characterized by motor symptoms such as, slowness of movement speed (bradykinesia), rest tremor, and rigidity, and the alterations in spatiotemporal parameters of gait can indicate bradykinesia in PD [4]. Gait analysis can also help distinguish PD patients with non-motor mental symptoms, showing that these patients exhibit a distinct gait pattern characterized by increased slowness and dynamic instability [5]. For this purpose, an extensive amount of research on gait analysis using several different methods has been published. These methods employ Inertial Measurement Units (IMUs), pressure sensitive electronic walkways, optical sensors, and RF sensors, such as radars, for gait analysis.

For gait evaluation using IMU sensors, the devices are typically attached to the lower limbs, such as the feet, shanks, ankles, or knees. An IMU unit includes gyroscope, accelerometer, and magnetometer sensors to collect data on velocity, acceleration, and positional information. Several research works have employed IMU sensors for gait parameters extraction [6]–[9]. For instance, an IMU-based gait study [10] involved attaching IMU sensors to the shanks of both legs of healthy participants, who were then asked to walk a 40-meter distance. Parameters such as stride time, stance time, swing time, step time, step length, stride length, and cadence were calculated.

Despite the high performance of IMU sensors, it can be challenging for patients to walk for long duration while wearing multiple sensors. In contrast, the RF sensors such as radars can measure gait parameters without direct contact with the human subject. For this purpose, a Frequency Modulated Continuous Wave radar is often used. An FMCW radar transmits electromagnetic signals with frequency linearly increasing with time. These radars are extensively used for gesture recognition [11], patient vital sign monitoring [3], activity recognition in long-term care facilities [12], posture estimation [13] and fall detection [14].

Seifert et al. [15] used a continuous wave radar along with a motion capture system to analyze the walking patterns of nineteen participants on a treadmill. Several gait parameters, including stride time, stride length, stance time, flight time, step time, step length, and cadence, were extracted. The errors were found to be negligible, although the study employed two radars. Similarly, walking patterns were also extracted using a doppler radar through trunk velocity and leg velocity. While step characteristics (step time and step length) remained same, the errors for stride-related measurements were higher when extracted using trunk velocity. Another study [16] employed FMCW radar to extract various parameters by mounting the radar on a treadmill and evaluated gait asymmetry. In a more recent study [17], gait asymmetry was evaluated using FMCW radar for both normal and induced abnormal walking. However, it is important to note that these methodologies were not tested on real patients.

In this paper, gait analysis of both healthy individuals and PD patients is performed using an FMCW radar. For all participants, the parameters step time, step length, step velocity, and cadence were extracted and compared with data obtained from IMU sensors. These parameters were collected within a six meters walking (three meters round-trip including

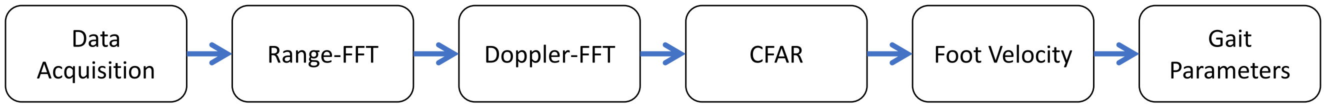


Figure 1. End-to-end block diagram for gait parameters extraction from FMCW radar.

turning point). Additionally, the measured parameters were compared between healthy individuals and PD patients to identify which parameters best describe the walking patterns of PD patients. Gait asymmetry was also evaluated using already established metric, and behavior of participants was analyzed on the turning point using radar. To the best of our knowledge, this study is the first to evaluate gait in real patients and observe the turning behavior using an FMCW radar.

The rest of the paper is organized as follows. Section II explains the proposed methodology, Section III describes the experimental setup, Section IV discusses the results and the conclusions are presented in Section V.

II. METHODOLOGY

This section discusses the proposed methodology of radar-based gait analysis in detail. Figure 1 gives an overview of the methodology.

A. Radar Signal Pre-processing

An FMCW radar emits electromagnetic waves with frequency which increases linearly in time, known as chirps. These transmitted signals have a base frequency known as (f_c) and sweep a bandwidth (B) defined by chirp's slope (S) and duration (T_c). The transmitted signal $x(t)$ can be mathematically represented as:

$$x(t) = exp(j2\pi(f_c t + \frac{B}{T_c}t^2)) \tag{1}$$

These chirps collide with a walking human present within the unambiguous range of the radar, and received at receiver antennas after a delay τ_d. To extract the velocity profile of the target human, multiple chirps are transmitted together in a frame. The reflected signals can be represented as:

$$y(t) = exp(j2\pi(f_c(t-\tau) + \frac{B}{T_c}(t-\tau_d)^2)). \tag{2}$$

All the received chirps are mixed with a copy of transmitted chirps to form a single-frequency signals, called Intermediate Frequency (IF) signal. The IF signals for each chirp frame are sampled and stored in a matrix and is further processed to extract different gait parameters.

B. Fast Fourier Transform (FFT) Processing

The two-dimensional matrix contains Analog to Digital Converter (ADC) samples for each IF signal. A Fast Fourier Transform (FFT) is performed on the ADC samples of each transmitted chirp to resolve the range of the target (range-FFT). Another FFT, known as Doppler-FFT is computed on number of chirps in a frame to find the velocity of the target. For range-FFT and Doppler-FFT, FFT sizes of 256 and 128 were used. In this way, a range-Doppler map is created for each frame.

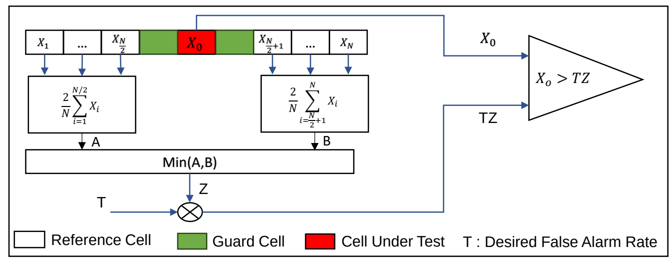
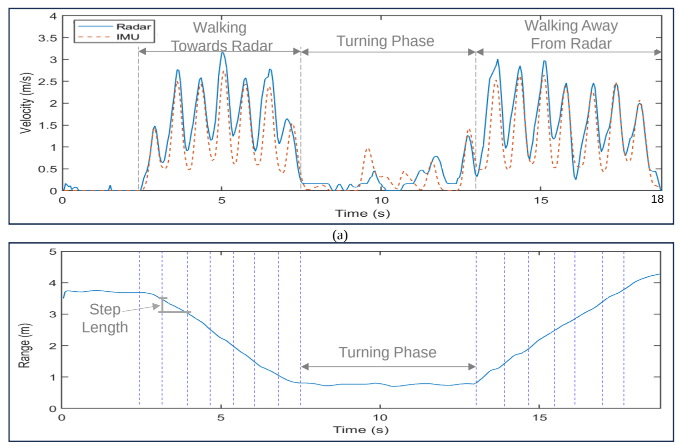


Figure 2. Working principle of CASO-CFAR detection.



(a)

(b)

Figure 3. Graphs representing (a) Changes in velocity of the participant measured from radar and IMU during complete walking cycle and (b) Range-time information from radar to measure step length identified through step time marked by consecutive minima in velocity-time graph.

C. Foot Velocity Extraction

After range-FFT and Doppler-FFT processing, the obtained range-Doppler maps contain reflections from human and multipath. So, a 2D Cell-Averaging Smallest of-Constant False Alarm Rate (CASO-CFAR) detection is applied to identify valid target reflections and neglect noise. The CASO-CFAR selects the smallest average from the left and right reference cells as noise level and compares it with signal present in Cell Under Test (CUT) using a desired false alarm rate [18]. The working principle of CASO-CFAR is also shown in Figure 2. In order to enhance the robustness, the CFAR was first applied in range dimension and then in Doppler dimension and only the targets confirmed in the second pass were selected. In our case, the number of reference cells and guard cells both were specified as 8. For a radar positioned at the feet of a human in motion, the foot velocity can be quantified by finding and accumulating the peak with the maximum velocity over time. For IMU sensor, the linear velocity is averaged from x,y and z-axis to obtain reference velocity. Figure 3 (a) show the foot velocity extracted from FMCW radar and IMU sensors.

D. Gait Parameters

In the foot velocity profile, the number of local peaks correspond to the number of steps. In the case of RF-based gait analysis technique, the toe-off and heel-strike cannot be differentiated properly. Hence, an estimate of gait parameters can be provided by identifying two consecutive local minima as toe-off and heel-strike events. Similar strategy was used to derive parameters from IMU sensors. Using this assumption, following spatio-temporal gait parameters can be measured:

1) Step Time: Step time refers to the duration of time taken for one complete step, usually measured in seconds. It is the time interval between the initiation of one foot's contact with the ground and the subsequent contact of the other foot. For the case of radar, step time can be measured by measuring the time difference between two consecutive minima in velocity profile, as expressed below,

$$T_{step}(i) = t_{HS}(i+1) - t_{HS}(i), \tag{3}$$

where $T_{step}(i)$ is the i_{th} step time, $t_{HS}(i)$ and $t_{HS}(i+1)$ are the times at which two consecutive minima in the velocity profile occur.

2) Step Velocity: Step velocity is the speed at which a person walks each step. It can be measured by averaging the instantaneous velocities in a single step.

$$V_{step} = \frac{1}{t}\sum_{n=1}^{t} V(n), \tag{4}$$

where V_{step} is the step velocity, $V(n)$ is instantaneous velocity at instant n, and t represent total number of sampling points within one step.

3) Step Length: Step length is the distance measured from the placement of one foot on the ground to the placement of the opposite foot. For radar, step length can be estimated from range-FFT by utilizing the step time measured previously, as shown in Figure 3 (b), and can be expressed as:

$$L_{step}(i) = r_{HS}(i+1) - r_{HS}(i), \tag{5}$$

where L_{step} is the step length of step i, $r_{HS}(i)$ and $r_{HS}(i+1)$ is the range of human body at two consecutive heel strikes.

TABLE I. DEMOGRAPHIC AND PHYSICAL CHARACTERISTICS OF STUDY PARTICIPANTS.

Parameter	Value
Age (years)	76.89±7.06
Sex (male)	55.5%
Height (m)	1.59±0.08
Weight (kg)	63.33±8.19

4) Cadence: Cadence refers to the number of steps taken per minute. In the case of radar, cadence can be computed by dividing the number of detected steps by total walking time. It is usually expressed as steps per minute (steps/min).

$$Cadence = \frac{\text{Number of Steps}}{\text{Total Walking Time}} \tag{6}$$

III. EXPERIMENTAL DETAILS

This section provide information about the participants, explains the detailed experimental design and configuration of radar and IMU sensors.

A. Participants

Ten patients diagnosed with PD, and ten control volunteered for the study. The additional information such as, age, sex, height and weight is listed in TABLE I in the form of mean±standard deviation. It was made sure that patients did not have any injury of lower limbs that caused any abnormal walking pattern, and that they could walk alone without assistance. All the participants signed a written consent form before taking the experiment.

B. Experimental Setup

The experiments were conducted in the corridor of university hospital. The experimental environment and the details of radar and IMU sensors used are presented in Figure 4(a). The radar was installed at 20cm height. The IMU sensor was also attached to each foot. The participants were asked to walk 3m towards radar, take a 180^o turn, and walk 3m again, towards initial starting point, in a continuous manner. The overall experimental setup including positioning of radar and IMUs, walking path and turning point is shown in Figure 4(b).

C. Radar and IMU Configuration

The radar used was Texas Instruments IWR6843ISK and E2box EBIMU24GV5 chipset was used as reference IMU sensor. Both the IMU unit and radar were properly synchronized by matching the starting time and any discrepancies were removed through received timestamps. The operating frequency of radar was 60 GHz and a bandwidth of 3.98 GHz was selected. The slow time sampling rate was 20 FPS and a total of 64 chirps were transmitted in a single frame. All the parameters for radar are listed in TABLE II. Depending on their walking speed, participants completed the walking path in varying duration. Therefore, the radar data capture time was initially set to 25 seconds and the data was later cropped to match the duration of each participant's walking. For IMU, the base frequency was 2.4 GHz and the sampling rate was 100 FPS which was later down-sampled to match with the radar.

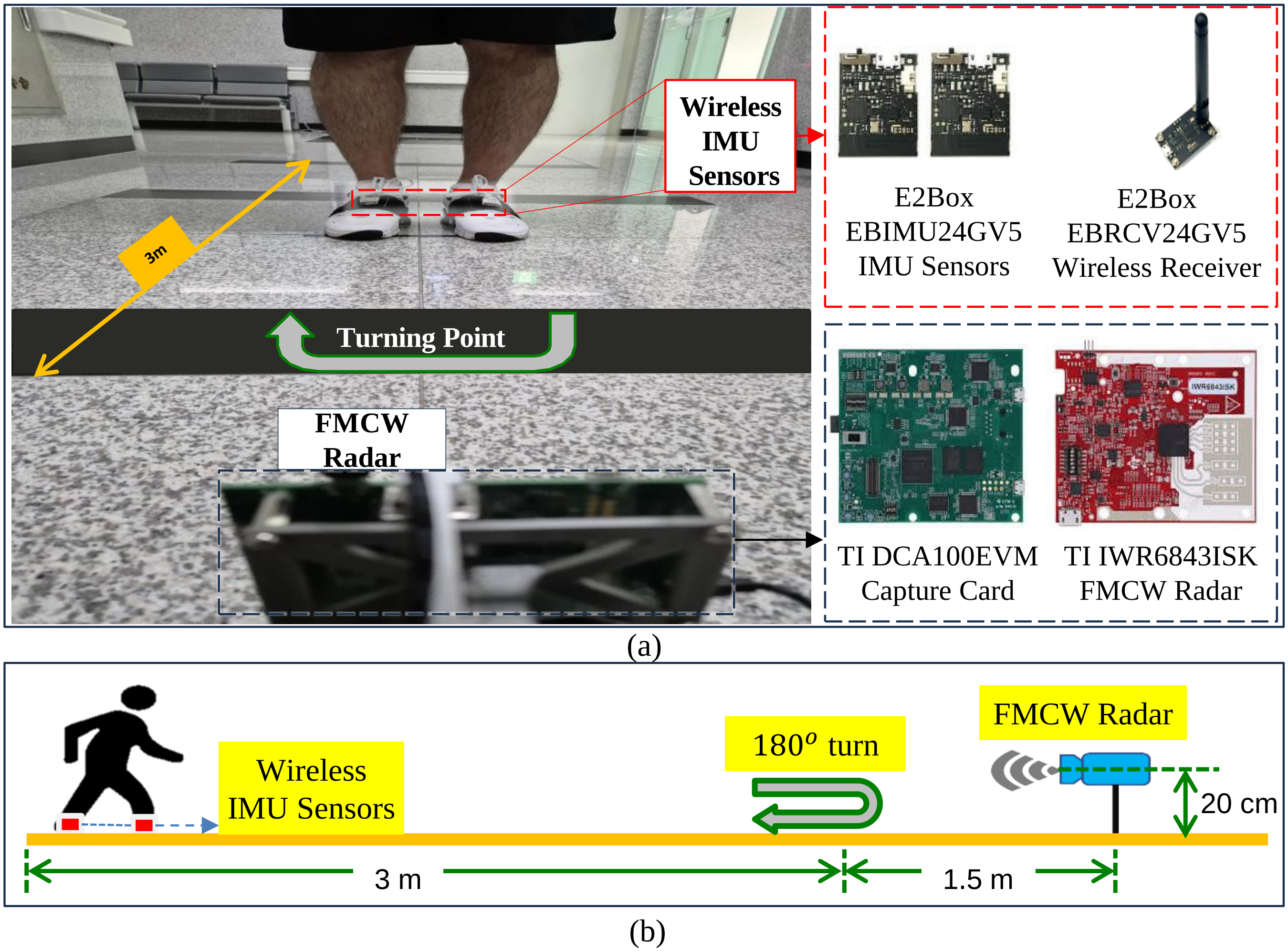


Figure 4. Experimental setup depicting (a) data capturing environment and detail of the employed sensors and (b) radar height, walking path, and turning point.

TABLE II. PARAMETERS USED FOR RADAR CONFIGURATION.

Parameter	Value
Operating Frequency	60 GHz
Sweep bandwidth	3.98 GHz
Number of frames / sec	20
Number of chirps / frame	64
ADC samples / chirp	128
Number of TX antenna	2
Number of RX antenna	4

IV. Results and Discussion

This section presents the obtained results and discusses the findings in detail.

A. Performance Comparison

After the extraction of gait parameters, the values for all the steps were compared with the reference and two error metrics, Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were calculated as follows,

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |A_t - F_t| \tag{7}$$

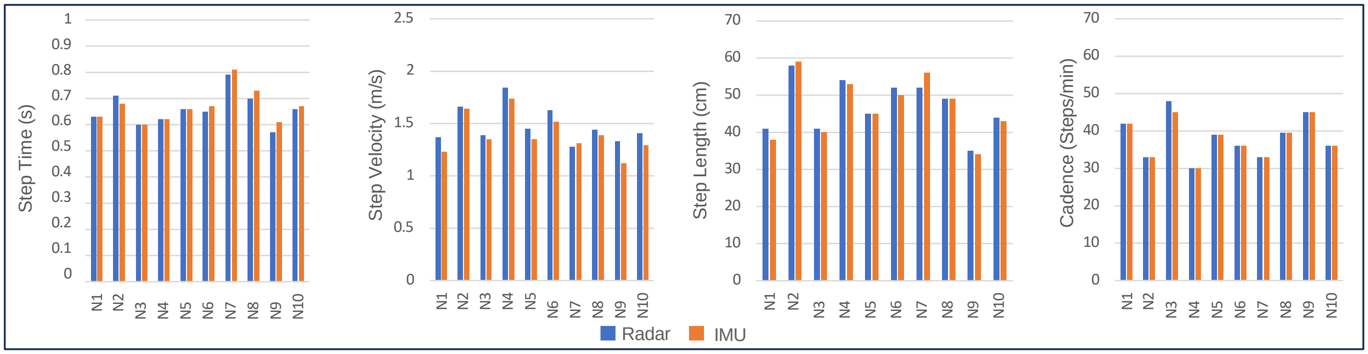
$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left|\frac{A_t - F_t}{A_t}\right| \times 100\% \tag{8}$$

where n is number of detected steps, A_t and F_t is actual (IMU) and predicted (radar) value of the gait parameter for t_{th} step.

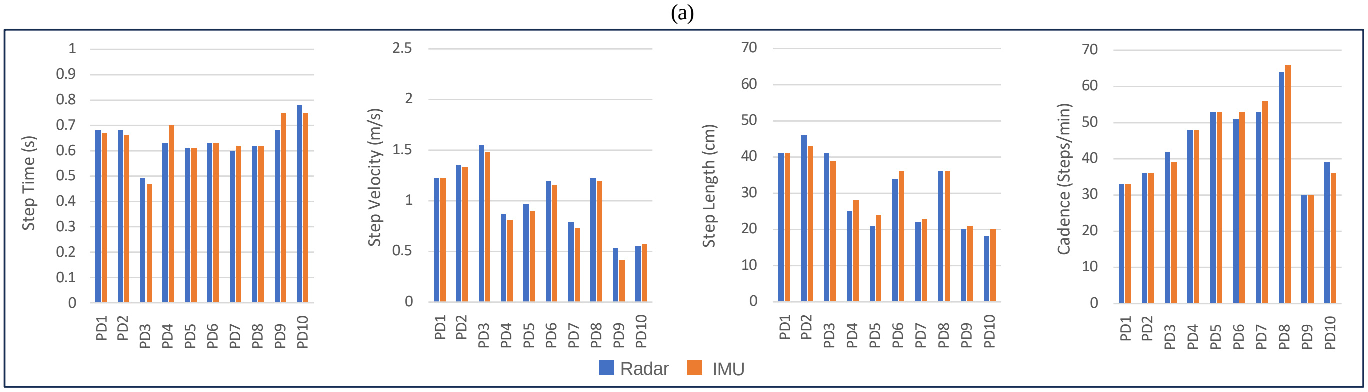
TABLE III. RESULTS OBTAINED FOR CONTROL GROUP.

Gait Parameter	Radar Value	IMU Value	MAE	MAPE (%)
Step Time (s)	0.66±0.46	0.67±0.06	0.06	8.32
Step Length (cm)	47.8±6.42	47.3±7.38	4.79	9.91
Step Velocity (m/s)	1.5±0.17	1.41±0.18	0.11	8.45
Cadence ($steps/min$)	38.56±6.19	38.56±6.19	0.80	2.08

The values obtained for step time, step distance, step velocity and cadence along with the errors are presented in TABLES III and IV, for control and patient group, respectively. By looking at the MAE, it can be seen that the control group showed slightly higher error rate in terms of step length and slightly lower error for the case of cadence, whereas similar



(a)



(b)

Figure 5. Graphs showing agreement of gait parameters (step time, step length, step velocity and cadence) extracted from radar and IMU for (a) control group and (b) patient group.

error rates were observed for step time and step velocity. However, the MAPE shows consistently higher error rates for PD patients for all the parameters, due to the fact that it depends heavily on the scale of the actual values. As the PD patients show smaller values of gait parameters than control group (except cadence), consequently, their percentage error appeared as higher, even for same MAE (as for the case of step velocity). Figure 5 shows mean values of all the gait parameters obtained from radar and IMU sensors for all the participants.

B. Unique Patterns between Control and Patient Group

Once the parameters were extracted, the values were compared among both groups using Mann-Whitney U-test and the p-values are listed in TABLE V. It was found that the control group exhibited significantly greater step length ($p<0.01$) and

TABLE IV. RESULTS OBTAINED FOR PATIENT GROUP.

Gait Parameter	Radar Value	IMU Value	MAE	MAPE (%)
Step Time (s)	0.63±0.05	0.64±0.05	0.06	9.43
Step Length (cm)	34.2±11.77	34±9.88	3.5	10.43
Step Velocity (m/s)	1.14±0.42	1.09±0.41	0.11	9.58
Cadence $(steps/min)$	48.76±12.1	48.39±12.22	1.72	3.56

TABLE V. COMPARISON OF RADAR-BASED GAIT PARAMETERS AMONG CONTROL AND PATIENT GROUP. THE PARAMETERS WITH AN ASTERISK(*) WERE FOUND TO BE STATISTICALLY SIGNIFICANT.

Parameter	Control Group	Patient Group	*p-value*
Step Time (s)	0.66±0.46	0.63±0.05	0.622
Step Length (cm)*	47.8±6.42	34.2±11.77	0.003
Step Velocity (m/s)*	1.5±0.17	1.14±0.42	0.002
Cadence (steps/min)	38.56±6.19	48.76±12.1	0.16
MAPE for Step Time (%)	8.32±2.61	9.43±3.98	0.97
MAPE for Step Length (%)	9.91±1.56	10.43±1.91	0.113
MAPE for Step Velocity (%)	8.45±1.76	9.58±2.21	0.678
MAPE for Cadence (%)	2.08±1.84	3.56±3.28	0.99

step velocity ($p<0.01$) while no considerable difference was found in terms of step time ($p>0.05$) and cadence ($p>0.05$). The patients suffering from PD can have limited range of motion of lower limbs, thereby reducing step (or stride) lengths and overall walking speed [19]. Additionally, for MAPE, no statistically significant difference was found in the control and the PD group. The average values for each each gait parameter for both groups are also shown in Figure 6.

C. Gait Asymmetry

The steps of all the participants were separated and the asymmetry between even and odd numbered steps was calculated using two different metrics, Symmetry Index (SI) [20]

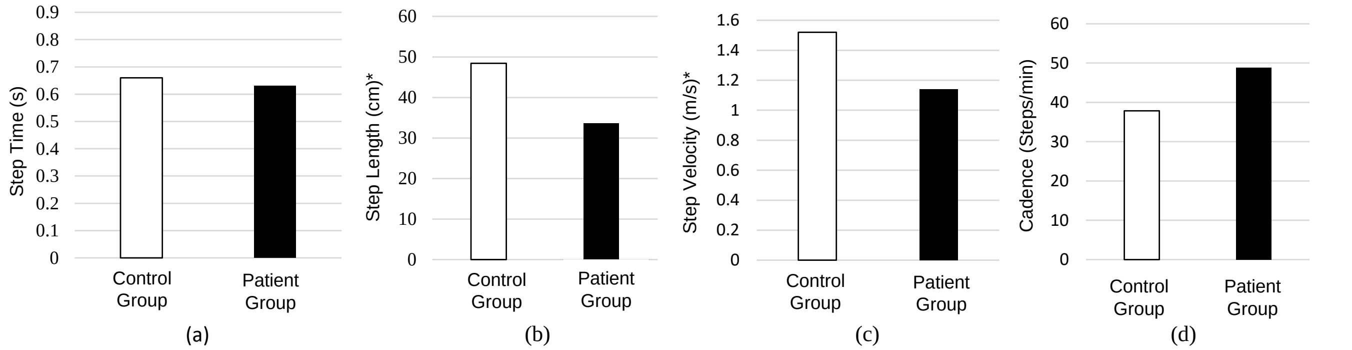


Figure 6. Comparison of gait parameters (a) step time, (b) step length, (c) step velocity, and (d) cadence, obtained from radar for the control and patient groups. Patient group exhibited smaller step length with lower step velocity and higher cadence than control group. The parameter with an asterisk(*) were found to be statistically significant (p<0.01).

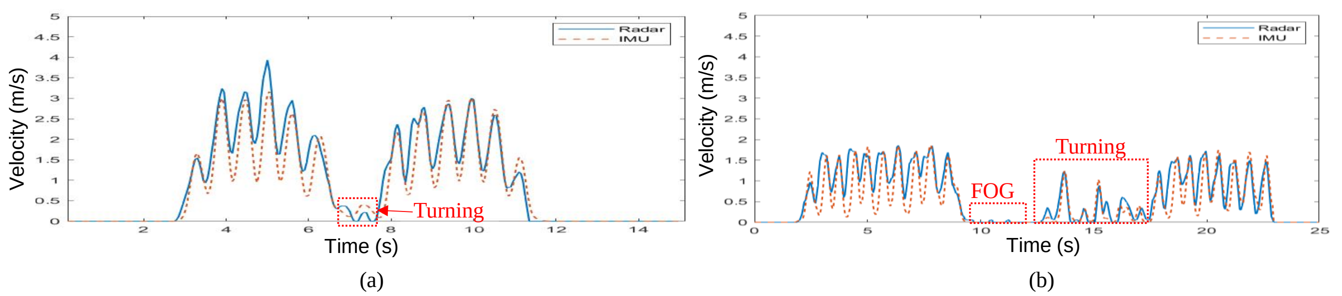


Figure 7. Velocity profiles of (a) healthy participant who took one single step quickly to complete the turn and (b) PD patient who suffered from Freezing of Gait (FOG) and took multiple steps.

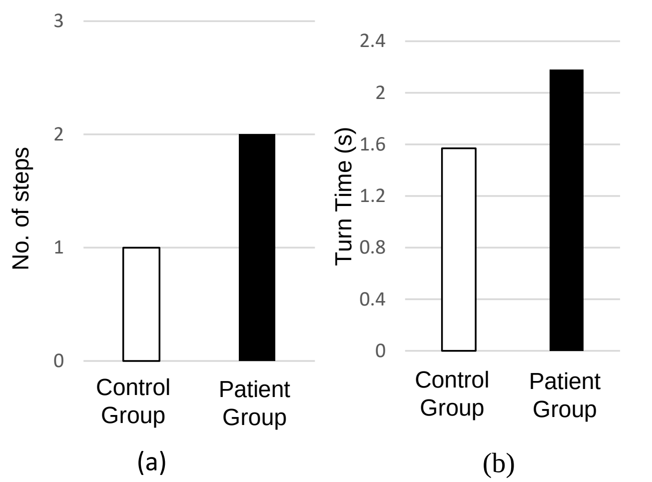


Figure 8. Comparison of (a) number of steps and (b) amount of time taken while turning. Patient group took more steps and time to complete the turn.

and Gait Asymmetry (GA) [21],

$$GA = |ln\{\frac{min(X_{even}, X_{odd})}{max(X_{even}, X_{odd})}\}| \times 100\% \tag{9}$$

$$SI = \frac{|X_{even} - X_{odd}|}{0.5(X_{even} + X_{odd})} \times 100\% \tag{10}$$

where X_{even} and X_{odd} refer to the average value of the gait parameter under consideration, for even and odd numbered step, respectively. A value of 0% indicate complete symmetry while 100% means complete asymmetry.

Using (9) and (10), the gait asymmetry and symmetry index was calculated for step time, step speed and step length. The use of the above two relations resulted in similar values. Subsequently, the statistical significance was also assessed between the control and PD groups using previously mentioned statistical test. The measure of gait asymmetry for both groups along with the p-values are presented in TABLE VI. It was found that patient group had higher step length asymmetry ($p<0.05$) and step velocity asymmetry ($p<0.05$) while no significant differences were found in step time asymmetry ($p>0.05$). The step length asymmetry in PD patients can be linked to reduced structural connectivity in the sensorimotor corpus callosum, compared to the control group [22].

TABLE VI. MEASURE OF GAIT ASYMMETRY FOR CONTROL AND PATIENT GROUP.

Gait Parameter	Control Group	Patient Group	*p-value*
Step Time GA(%)	9.87±6.01	7.64±5.07	0.39
Step Length GA(%)	9.57±7.16	24.45±12.57	0.02
Step Velocity GA(%)	3.15±2.58	8.21±9.81	0.04

D. Turning in Control and Patients Group

Mostly, research on gait analysis in individuals with PD emphasizes straight-line walking, however, turning difficulties are an early indicator of PD progression as individuals with PD require more time and steps to complete a turn [23]. Hence, analysis of turning behavior can provide meaningful insight into the health of PD patients. For radar, the starting of the turning phase can be marked through a sharp reduction in velocity while the end of turning can be recognized through multiple consecutive high velocity peaks in the velocity-time plot. In this way, the turning phase was analyzed for healthy and patient's data. Figure 7 shows an example of turning phase identification for one healthy subject and one patient.

After identifying the turning phases, the number of steps and time was measured for both groups and a graph was plotted. Figure 8 (a) shows the number of steps and Figure 8 (b) shows the time taken while turning for both control group and patient group. It can be seen that the patient group took more steps and longer time to turn. The turning ability in PD can be hindered by limited trunk flexibility, problems with turn coordination, freezing episodes, and balance issues [24], therefore, they complete the turn in multiple steps in order to avoid fall [23].

V. Conclusion

This study demonstrates the potential of FMCW radar in measuring gait parameters for individuals with PD and healthy controls. The analysis focused on four key gait parameters namely step time, step length, step speed, and cadence. On comparing the performance of radar data with IMU sensor, the results show a MAPE of 8.8% for step time, 10.17% for step length, 9.01% for step speed, and 2.82% for cadence.

Additionally, the study highlights the radar's ability to detect gait asymmetry and analyze walking patterns at the turning point. These findings suggest that the FMCW radar can serve as a viable, non-invasive tool for gait monitoring in daily living scenarios, potentially aiding in early intervention and better management of PD.

Acknowledgment

This study was supported by the National Research Foundation (NRF) of South Korea (NRF-2022R1A2C2008783). This study received approval for all ethical and experimental procedures from the Institutional Review Board on Human Subjects Research and Ethics Committees at Hanyang University in Seoul, South Korea, under Approval No. HYUH 2023-10-035-004.

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