Inertial-based gait metrics during turning improve the detection of early-stage Parkinson's disease patients

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***Abstract*— Patients with early-stage Parkinson's disease (PD) exhibit various but subtle motor symptoms, especially postural instability and gait disorders (PIGD). Patients show deteriorated gait performance at turns as the complex gait task requires more limb coordination and postural stability control, which may help to discriminate signs of early PIGD. In this study, we firstly proposed an IMU-based gait assessment model for quantifying comprehensive gait variables in both straight walking and turning tasks from five domains: respectively gait spatiotemporal parameters, joint kinematic parameters, variability, asymmetry, and stability. Twenty-one patients with idiopathic Parkinson's disease at the early stage and nineteen age-matched healthy elderly adults were enrolled in the study. Each participant wore a full-body motion analysis system with 11 inertial sensors and walked along a path consisting of straight walking and 180-degree turns at a self-comfortable speed. A total of one hundred and thirty-nine gait parameters were derived for each gait task. We explored the factor effect of group and gait tasks on gait parameters using a two-way mixed analysis of variance. The discriminating ability of gait parameters between PD and the control group was evaluated using receiver operating characteristic analysis. Sensitive gait features were optimally screened (AUC$>$0.7) and categorized into 22 groups to classify PD and healthy controls based on a machine learning method. Results demonstrated that PD patients exhibited more gait abnormalities at turns, especially on the RoM and stability of the neck, shoulder, pelvic, and hip joints compared to the healthy control group. These gait metrics have good discriminating abilities to identify early-stage PD (AUC$>$0.65). Moreover, the inclusion of gait features at turns can significantly improve the classification accuracy compared to that only used parameters during straight walking. We show that quantitative gait metrics during turning have great potential to be used for enhancing early-stage PD detection.**

***Index Terms*— inertial measurement units, gait assessment model, Parkinson's disease detection, quantitative gait metrics, turning.**

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I. Introduction

POSTURAL instability and gait disorder (PIGD) is one of the main motor symptoms in patients with Parkinson's disease (PD) [1]. The current diagnosis in clinic is usually based on subjective measures derived from observations by doctors to generate a score of the Unified Parkinson's Disease Rating Scale (UPDRS) where diagnosis of PD at early-stage can be difficult because patients would manifest various and subtle motor symptoms [2], [3]. A quantitative and comprehensive model for gait assessment is required for better diagnosis of the motor symptoms.

Gait analysis systems including optical motion capture systems and instrumented walkways have been employed in assessment of gait characteristics of PD patients [4]–[7]. Previous studies investigated PD patients' joint kinematics during straight walking [8]–[11] and found that patients performed the reduced range of motion of hip and knee joints [12]. Various spatiotemporal gait variables measured by these systems are analyzed from different domains, such as pace (e.g., step length, walking speed), rhythm (e.g., step time), variability, asymmetry, and posture control (e.g., step width) [4], [5]. These quantitative gait parameters have been considered to evaluate the disease progression and treatment response of PD patients. Although the laboratory-based systems can provide precise measurements, the high cost and restricted laboratory environment limited their clinic applications. Wearable inertial measurement unit (IMU) is a potential solution to evaluate gait performance outside a laboratory environment.

PD patients showed deteriorated gait performance during complex gait tasks, such as turning [13]–[15]. Huxham et al. [6] observed abnormal rotation amplitude and rotation sequence of the head, thoracic and pelvis in early-stage PD patients during 60 degrees and 120 degree turns. Mild to moderate PD patients exhibited narrower step width, smaller pelvic displacement and reduced lateral stability at 180 degree turns [17]. The impaired limb coordination and poorer postural stability during turning lead to a decreased stride velocity, longer duration and more stride number compared to healthy controls [18]–[20]. Therefore, evaluation of turning performance can contribute to discriminate PIGD at early stage.

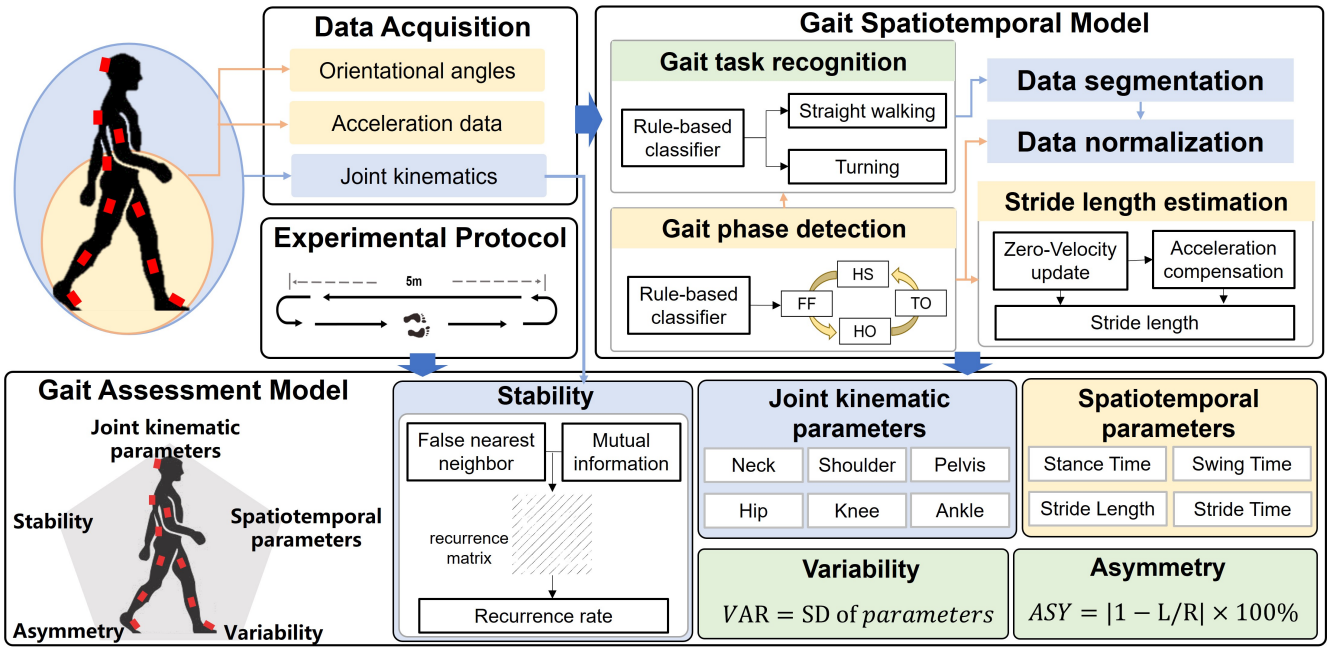

Fig. 1. Layout of the gait assessment model.

Previous studies have only considered global turning characteristics in IMU-based models. Morris et al. [21] developed a gait and balance model in which characteristics in turning are analyzed as an independent domain beside with pace, rhythm and variability domains. Vitorio et al. [22] quantified 26 gait parameters in four gait domains, including the upper body, the lower body, turning and variability based on wearable devices. A correlation between turning and cognitive function is observed in PD patients indicating turning performance is sensitive to cognitive decline and the worsening neuronal control may deteriorate gait performance in early-stage PD. Global turning characteristics, such as velocity, number of steps, and turn duration, have been commonly investigated. However, detailed characterization on turning abnormality in terms of gait spatiotemporal parameters and joint kinematics, is not yet to be discussed in an IMU-based gait assessment model.

One aim of this study is to propose an IMU-based gait assessment model for quantifying comprehensive gait variables in both straight walking and turning. The gait spatiotemporal parameters and joint kinematics are estimated and the variability, asymmetry and stability are furtherly calculated. A total of one hundred and thirty-nine metrics are extracted for analyzing gait and balance ability. Furthermore, twenty-one patients with idiopathic PD at the early stage and nineteen age-matched healthy elder adults were recruited in this study. Quantitative gait metrics that can discriminate early-stage PD patients from healthy elderly group during straight walking and turning were investigated.

II. Inertial-based Gait Assessment Model

Based on the spatiotemporal gait model in our previous work [23], we further proposed an inertial-based gait assessment model that enables quantifying participant's gait performance in both straight walking and turning from five domains: gait spatiotemporal parameters, joint kinematic parameters, variability, asymmetry, and stability, as shown in Fig.1.

A. Gait spatiotemporal parameters

Gait temporal parameters, including stride time (StrT), stance time (StaT), and swing time (SwiT), were calculated based on the spatiotemporal gait model [23], which included algorithms for gait phase detection, gait task recognition, and stride length estimation. The pitch angles of the foot and shank were used to detect four gait events, namely heel strike (HS), flat foot (FF), heel off (HO), and toe off (TO), based on a rule-based machine learning method. Two consecutive HS of ipsilateral foot were used to identify gait cycles, while TO was used to divide a gait cycle into stance and swing phases. A double integration method that consists of a zero-velocity update (ZVU) approach with acceleration compensation was employed to estimate stride length (StrL) based on the acceleration data measured from the foot segment. Moreover, gait tasks (straight walking and turning) were classified based on gait cycles according to the course angle changes between HO and successive HS events.

All parameters were normalized with the subject's height as (1) [24]:

$$SP_{norm} = \frac{SP}{H}$$
$$TP_{norm} = \frac{TP}{\sqrt{H/g}} \quad (1)$$

Where SP and TP represents spatial and temporal parameters respectively, H represents subject's height, g represents the gravitational acceleration ($9.81m/s^2$).

B. Joint kinematic parameters

Joint angles of the neck, shoulder, pelvis, hips, knees and ankles were calculated using a motion analysis model (Noraxon MyoMotion software V.3.16, Noraxon, USA). The joint kinematic trajectories were segmented and normalized to 101 samples based on gait cycles. The range of motion (RoM) of joints was then calculated.

C. Variability

Gait variability was defined as standard deviation of spatiotemporal gait parameters and joint angular RoMs.

D. Asymmetry

The asymmetry coefficients of gait spatiotemporal parameters and joint kinematic parameters were calculated following the below equation:

$$ASY = |1 - \frac{L}{R}| \times 100\%. \quad (2)$$

Where L and R represents parameters for the left and right side respectively.

E. Stability

Recurrence quantification analysis (RQA) was used to evaluate joint kinematic stability [25], [26]. The normalized joint angular trajectories were embedded in m dimensions state spaces (according to the false nearest neighbour method) with each dimension shifted in time by integer multiples of t samples (according to the first minimum mutual information function). The Euclidean distances between all embedded vectors were calculated to obtain a distance matrix. A recurrence matrix was created by selecting a threshold of 10% of the max distance where all cells with values below this threshold were identified as recurrent points. Percent of recurrent points in the recurrence matrix, so named recurrence rate (RR), was calculated to represent dynamic stability for joint movements.

It needs to be mentioned that all the above-mentioned parameters were evaluated for straight walking and turning respectively. As a participant completed five cycles of "5-meters straight walking - 180° turning - 5-meters straight walking - 180° turning", ten data segments for straight walking and nine data segments for turning can be divided. Two consecutive gait cycles were derived during a data segment of straight walking to eliminate the effect of gait transition.

III. Experimental Setup

A. Participants

Twenty-one patients with idiopathic PD at the early stage (Hoen&Yahr 1-2) and nineteen age-matched healthy controls (HC) participated in this study. Patients were enrolled by neurologists from the outpatient clinic of the Department of Neurology at Tianjin Huanhu Hospital. Inclusion criteria were: 1) aged 50-70; 2) diagnosed as idiopathic PD, Hoen&Yahr stage 1-2; and 3) capable to walk independently for more than 10 minutes. Exclusion criteria included: 1) had deep brain stimulation (DBS) surgical intervention; 2) had musculoskeletal injuries or other neurological diseases that would restrict ambulation; 3) a Mini-Mental State Examination (MMSE) score<24. The inclusion criteria of the healthy control group were the elderly aged 50-70, and the exclusion criteria were: 1) had musculoskeletal injuries or other neurological diseases that would restrict ambulation; 2) had received brain surgery; 3) had dementia symptoms, a Mini-Mental State Examination (MMSE) score<24. This study was approved by the Ethics Committee of Tianjin Huanhu Hospital.

TABLE I
SUMMARY OF PARTICIPANTS' DEMOGRAPHIC INFORMATION

	PD (n=21)	HC (n=19)	p value
Sex (M/F)	12/9	7/12	0.199[a]
Age (year)	64.11±7.04	63.37±5.75	0.166[b]
Height (m)	1.67±0.08	1.62±0.06	0.067[b]
Weight (kg)	67.29±9.74	63.57±8.51	0.143[b]
MMSE (score)	28.00±1.41	28.15±1.72	0.454[a]
MoCA (score)	24.70±3.16	26.63±1.43	0.088[a]
UPDRS III (score)	17.12±10.72	-	-
H&Y (stage)	1.47±0.48	-	-
Disease duration (years)	2.66±2.21	-	-

[a]Chi-squared test, [b]Mann-Whitney U test.

B. Experiemental protocol

As shown in Fig.2(a), a participant wore a wearable full-body motion analysis system (Research Pro IMU, Noraxon USA, Inc., Scottsdale, AZ, USA) consisting of 11 IMU sensors attached to the head, upper thoracic, pelvic, upper arms, thighs, shanks, and feet of both sides. Three-dimensional earth-based acceleration, orientational angles of body segments and joint kinematics were recorded at a sampling rate of 100 Hz with the use of the myoMOTION^{TM} software.

Participants were asked to walk along a path traced on the floor with tape at their comfortable walking speed for five cycles, Fig.2(b). All PD patients were tested in their medication ON condition.

C. Statistic analysis

A total of one hundred and thirty-nine gait parameters were extracted for each gait task. A two-way mixed analysis of variance (ANOVA) was used to investigate the factor effect of group (PD/HC) and gait tasks (straight walking and turning) on gait metrics. An independent sample T-test was furtherly used to investigate the significant difference in gait parameters between PD and HC. SPSS (IBM V.25) was used for statistical analysis. Receiver operating characteristic (ROC) analyses and the area under the curve (AUC) of the ROC curves were conducted to evaluate the discriminating ability of gait parameters to identify early-stage PD and HC. The R software (R V.3.6.1) was used for the ROC analyses. Statistical significance was set at $p<0.05$.

D. Classification

The influence of gait tasks and IMU sensor combination on identification of early-stage PD was investigated. The

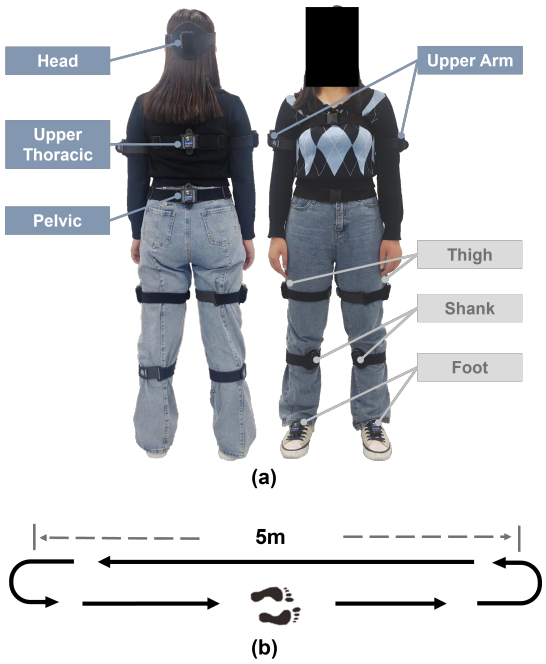

Fig. 2. Experimental setup. (a) A participant wore IMU sensors attached to the head, upper thoracic, pelvic, upper arms, thighs, shanks, and feet of both sides. (b) Participants performed "straight walking - turning - straight walking back - turning" along a path traced on the floor at their comfortable walking speeds.

discriminative gait parameters (AUC>0.7) were categorized into 22 groups based on gait tasks (straight walk, turn, and both gait tasks) and gait parameter types (gait spatiotemporal related parameters, kinematics related parameters of individual joints, all joint kinematics related parameters, all gait parameters). Support vector machine (SVM) with linear kernel was used and the C-SVM was selected by 5-fold cross-validation. The above-mentioned data procedure was carried out using MATLAB software (The Mathworks, Natick, MA, USA). Recognition accuracy when 22 groups of gait parameters employed was calculated and compared using Kruskal-Wallis test.

IV. Results

A. Gait spatiotemporal related parameters

As shown in Table.II, the gait task had a significant effect on most gait spatiotemporal related parameters despite swing time and stance time asymmetry. Compared to straight walking, both groups performed significantly decreased stride length and increased stride time and stance time during turning while variability and asymmetry of gait spatiotemporal parameters were higher than those in straight walking. PD patients had decreased stride length in both gait tasks (straight walking: L $p<0.001$, R $p=0.003$, turning: L $p=0.001$ R $p=0.001$), as shown in Fig.3(a). The stride time asymmetry and stance time asymmetry were significantly different between the two groups (asymmetry of StrT: $p=0.020$, asymmetry of StaT: $p=0.012$) while the variability of stride time and stance time only showed significant difference on the right side during turns, Fig.3(b).

TABLE II
TWO-WAY MIXED ANOVA OF SPATIOTEMPORAL RELATED PARAMETERS OF PD AND HC DURING STRAIGHT WALKING (SW) AND TURNING (T).

		Stride Length	Stride Time	Stance Time	Swing Time
L	PD_SW	0.65±0.07	2.61±0.24	1.84±0.20	0.77±0.05
	PD_T	0.41±0.07	2.81±0.33	2.01±0.29	0.80±0.07
	HC_SW	0.74±0.06	2.72±0.15	1.91±0.12	0.81±0.03
	HC_T	0.48±0.06	2.87±0.22	2.02±0.17	0.85±0.06
	Group	***<0.001***	0.300	0.555	***0.002***
	Task	***<0.001***	***<0.001***	***<0.001***	0.053
	Interaction	0.508	0.404	0.256	0.830
R	PD_SW	0.65±0.07	2.61±0.22	1.82±0.19	0.78±0.06
	PD_T	0.51±0.05	2.79±0.33	1.98±0.28	0.81±0.07
	HC_SW	0.74±0.06	2.72±0.15	1.90±0.13	0.82±0.04
	HC_T	0.59±0.07	2.86±0.24	2.01±0.2	0.85±0.05
	Group	***0.001***	0.280	0.170	***0.001***
	Task	***<0.001***	***<0.001***	***0.019***	0.084
	Interaction	0.409	0.431	0.685	0.930
Variability (L)	PD_SW	0.01±0.01	0.05±0.03	0.04±0.03	0.01±0.01
	PD_T	0.06±0.02	0.08±0.05	0.07±0.04	0.03±0.02
	HC_SW	0.01±0.00	0.04±0.01	0.04±0.01	0.01±0.00
	HC_T	0.07±0.02	0.08±0.05	0.07±0.05	0.02±0.01
	Group	0.757	0.767	0.861	0.370
	Task	***<0.001***	***<0.001***	***0.001***	***<0.001***
	Interaction	0.603	0.682	0.653	0.808
Variability (R)	PD_SW	0.01±0.01	0.05±0.03	0.05±0.03	0.01±0.01
	PD_T	0.05±0.02	0.19±0.14	0.19±0.15	0.03±0.02
	HC_SW	0.01±0.00	0.03±0.02	0.03±0.02	0.01±0.00
	HC_T	0.05±0.02	0.08±0.05	0.08±0.05	0.02±0.01
	Group	0.719	***0.040***	***0.018***	0.234
	Task	***<0.001***	***<0.001***	***<0.001***	***<0.001***
	Interaction	0.429	0.864	0.837	0.810
Asymmetry	PD_SW	2.53±1.13	1.50±0.78	2.98±1.18	3.17±2.05
	PD_T	21.74±10.61	6.41±8.42	9.36±12.66	6.37±5.37
	HC_SW	1.87±0.64	1.02±0.62	2.24±0.93	3.72±1.86
	HC_T	19.67±4.98	2.40±1.69	3.90±3.30	5.10±2.27
	Group	0.357	***0.020***	***0.012***	0.657
	Task	***<0.001***	***<0.001***	0.088	***<0.001***
	Interaction	0.653	0.860	0.726	0.328

Significant differences ($p<0.05$) are indicated in bold and italics.

B. Joint kinematics related parameters

The gait task factor had a significant effect on joint kinematics. Both groups exhibited increased RoM of the neck and pelvis joints as well as reduced RoM of the rest in the sagittal plane during turning. Participants reduced shoulder rotation and increased rotation of the rest of the joints to establish turns. The RoM of lateral neck angle, right shoulder abduction and right pelvis obliquity were significantly increased during turning when participants had higher variability for most joints. The RoM asymmetry of the neck axial angle was decreased and the RoM asymmetry of the right pelvic obliquity and lower limb joint flexion were significantly increased for turns. It is interesting to see that both groups exhibited increased stability of the trunk and pelvis while reduced stability of lower limbs, as shown in Table.IV.

Patients with PD had significantly reduced flexion RoMs of hip and knee as well as RoM variables of shoulder rotation in both gait tasks. PD patients decreased RoM of neck lateral angle and shoulder abduction during straight walking while reduced rotation of neck, pelvis, and hip compared to the control group during turning, Fig.3(f)-(g). The RoM variability of neck lateral angle, left pelvis tilt and right hip rotation angles was significantly different between the groups (RoM variability of lateral neck angle: L $p<0.001$, R $p<0.001$, RoM

TABLE III

TWO-WAY MIXED ANOVA OF THE UPPER BODY JOINT KINEMATICS RELATED PARAMETERS OF PD AND HC DURING STRAIGHT WALKING (SW) AND TURNING (T).

		Shoulder			Neck			Pelvic		
		Sagittal plane	Coronal plane	Horizontal plane	Sagittal plane	Coronal plane	Horizontal plane	Sagittal plane	Coronal plane	Horizontal plane
RoM (L)	PD_SW	15.97±8.54	5.79±3.3	14.03±5.43	6.52±1.62	2.57±0.76	6.43±2.59	4.5±1.14	6.07±1.52	7.56±2.25
	PD_T	12.45±6.76	5.55±3.2	12.44±5.63	7.63±2.31	3.11±1.01	11.43±4.94	5.2±1.73	5.95±1.67	9.23±3.1
	HC_SW	23.18±8.91	9.3±4.1	28.76±14.46	7.14±2.83	4.33±1.39	7.92±2.28	4.25±1.37	6.08±2.31	8.13±4.09
	HC_T	16.15±5.41	8.19±3.98	24.82±10.5	10.84±3.23	5.57±2.35	17.1±5.64	6.06±1.41	6.66±1.66	13.87±4.51
	Group	0.057	***0.012***	***<0.001***	***0.028***	***<0.001***	***0.010***	0.581	0.533	***0.027***
	Task	***<0.001***	0.272	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***0.001***	0.382	***<0.001***
	Interaction	***0.018***	0.474	0.098	***0.001***	0.076	0.544	***0.044***	0.185	***0.001***
RoM (R)	PD_SW	17.25±11.36	5.75±4.64	13.78±8.5	5.87±1.49	2.54±0.84	5.16±2.3	4.03±1.04	6.05±1.64	6.29±2.02
	PD_T	15.14±10.21	8.05±7.3	11.97±6.61	7.33±2	3.25±1.24	12.08±4.52	5.09±1.44	4.78±1.45	9.84±2.84
	HC_SW	21.15±7.63	7.81±3.91	21.8±9.34	7.23±2.78	4.32±1.37	7±2.01	4.34±1.63	6.05±2.26	7.19±3.1
	HC_T	18.78±6.77	11.79±5.05	17.99±5.99	10.14±2.68	5.66±2.24	17.28±5.42	6.49±1.87	5.05±1.26	14.65±3.92
	Group	0.247	***0.001***	***0.012***	***0.009***	***<0.001***	***0.013***	0.109	0.810	***0.006***
	Task	***0.011***	***0.008***	***0.001***	***<0.001***	***0.047***	***<0.001***	***<0.001***	***<0.001***	***<0.001***
	Interaction	0.877	0.472	0.186	***0.022***	0.906	0.947	0.279	0.512	***<0.001***
Variability of RoM (L)	PD_SW	1.38±1.49	0.5±0.39	1.31±1.43	1.51±0.95	0.29±0.12	1.25±1.05	0.48±0.24	0.3±0.19	0.98±0.45
	PD_T	1.32±0.85	0.71±0.57	1.4±1.13	1.54±0.89	0.46±0.19	2.11±1.2	0.75±0.44	0.93±0.5	1.33±0.67
	HC_SW	1.68±1.18	1.03±1.03	2.13±1.37	1.38±0.94	0.65±0.18	1.75±1.32	0.58±0.24	0.32±0.11	1.08±0.64
	HC_T	2.44±1.68	1.34±1.16	2.44±1.1	2.46±1.08	0.93±0.41	2.7±0.9	1.11±0.31	0.83±0.46	1.44±0.64
	Group	0.189	0.079	0.062	0.221	***<0.001***	***0.035***	***0.012***	0.672	0.527
	Task	0.167	0.116	0.271	***0.033***	***0.015***	***<0.001***	***<0.001***	***<0.001***	***0.008***
	Interaction	0.672	0.993	0.913	***0.035***	0.512	0.832	0.263	0.543	0.963
Variability of RoM (R)	PD_SW	0.99±0.62	0.43±0.26	0.9±0.55	1.11±0.9	0.25±0.17	0.99±0.9	0.32±0.11	0.25±0.13	0.66±0.23
	PD_T	1.85±1.43	1.03±0.55	1.43±0.97	1.62±0.65	0.55±0.32	2.47±1.23	0.96±0.55	0.71±0.36	2.22±1.28
	HC_SW	1.56±0.86	1.25±1.9	1.15±0.67	1.48±0.88	0.53±0.26	1.17±0.74	0.5±0.27	0.41±0.18	0.91±0.41
	HC_T	2.33±1.61	1.32±0.69	1.85±0.92	2.34±1.17	0.85±0.37	3.48±1.32	1.16±0.51	0.83±0.41	2.65±1.42
	Group	0.052	0.067	0.065	0.054	***<0.001***	0.154	0.093	0.092	0.198
	Task	***0.012***	***<0.001***	***0.006***	***0.003***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***
	Interaction	0.775	0.750	0.780	0.926	0.532	0.652	0.896	0.744	0.689
Asymmetry of RoM	PD_SW	90.76±106.05	61.42±83.16	68.76±53.72	19.47±11.19	13.51±6.77	34.33±27.38	16.33±9.07	8.93±6.15	24.1±14.18
	PD_T	68.39±68.25	50.97±42.88	53.09±36.55	20.46±10.69	17.06±9.28	21.15±6.89	17.91±13.72	29.14±17.74	21.93±7.89
	HC_SW	46.33±35.08	62.44±38.16	57.59±32.93	22.81±8.25	13.61±4.71	28.34±10.23	13.71±6.95	6.39±3.35	19.88±8.48
	HC_T	41.46±17.58	34.42±16.59	57.97±33.42	24.99±8.45	21.33±14.1	22.45±7.9	17.59±9.33	38.82±19.62	18.88±5.08
	Group	0.166	0.819	0.809	0.053	0.484	0.420	0.778	0.311	0.206
	Task	0.861	0.289	0.405	0.519	0.055	0.033	0.468	***<0.001***	0.697
	Interaction	0.705	***0.044***	0.544	0.851	0.926	0.707	0.324	0.081	0.832
Stability (L)	PD_SW	6.84±1.88	5.1±1.48	4.97±1.23	7.45±4.56	4±1.58	10.49±7.83	4.72±0.69	4.81±1.72	7.28±1.18
	PD_T	5.57±1.75	4.39±1.07	4.06±0.96	9.09±4.21	5.26±1.55	10.13±2.15	6.39±2.61	5.57±2.03	6.82±2.02
	HC_SW	9±1.77	6.39±2.35	6.37±1.19	7.48±3.5	4.01±1.09	8.66±3.61	4.56±0.93	4.39±1.69	6.39±1.23
	HC_T	7.22±1.6	6.19±1.61	5.9±1.23	11.96±4.49	6.57±1.82	11.7±3.04	9.64±2.5	6.35±1.47	7.67±1.92
	Group	***0.001***	***0.005***	***<0.001***	0.150	0.135	0.677	***0.003***	0.737	0.840
	Task	***<0.001***	0.155	***0.001***	***0.004***	***<0.001***	***0.003***	***<0.001***	***0.004***	0.648
	Interaction	0.425	0.417	0.254	0.324	0.245	0.217	***0.001***	0.185	***0.021***
Stability (R)	PD_SW	7.17±2.06	4.97±1.64	4.73±1.72	6.83±4.88	3.85±1.4	8.23±4.26	4.24±0.56	4.95±1.79	5.89±1.14
	PD_T	6.5±2.31	5.98±1.71	4.06±1.52	9.51±4.16	5.03±1.3	10.91±2.13	6.59±2.73	4.81±1.47	8.29±2.55
	HC_SW	8.06±1.71	6.4±3.72	6.24±1.59	7.4±3.92	4.04±0.86	7.12±2.71	4.53±1.18	4.43±1.97	6.12±1.5
	HC_T	8.82±4.1	7.58±2.02	6.04±1.02	12.67±4.49	6.16±1.54	12.19±2.39	9.25±2.44	5.39±0.94	8.37±1.71
	Group	***0.022***	***0.032***	***<0.001***	0.101	0.088	0.840	***0.010***	0.778	0.737
	Task	0.277	***0.003***	0.301	***<0.001***	***<0.001***	***<0.001***	***<0.001***	0.088	***<0.001***
	Interaction	0.697	0.696	0.442	0.472	0.582	0.269	***0.010***	0.054	0.872

Significant differences (p<0.05) are indicated in bold and italics.

variability of left pelvis tilt: p=0.012, RoM variability of right hip rotation: p<0.001). PD patients had lower RoM variability of neck lateral angle in both tasks but only performed lower variability of left pelvic tilt and right hip rotation at turns as shown in Fig.3(c). Moreover, the interaction effects were significant on the variability of left neck flexion and right hip abduction (shown in Table.III and Table.IV). PD patients were not different from HC on the variability of left neck flexion and right hip abduction during straight walking, but significantly reduced left neck flexion variability and increased right hip abduction variability at turns.

Results showed that the stability of the shoulder and hip rotation of the PD patients was significantly smaller than HC in both tasks and patients' postural stability was furtherly worsened during turning. The group exhibited reduced stability of shoulder angles, pelvis tilt and right knee flexion in turns, Fig.3(d)-(e).

C. The discriminating ability of gait parameters

As shown in Fig.4(a), the AUCs of stride length in both tasks and swing time during straight walking were greater than 0.7. The variability of stride time and stance time during turning showed a good sensitivity between the PD and HC (AUC: StrT = 0.641, StaT = 0.665).

TABLE IV

TWO-WAY MIXED ANOVA OF THE LOWER BODY JOINT KINEMATICS RELATED PARAMETERS OF PD AND HC DURING STRAIGHT WALKING (SW) AND TURNING (T).

		Hip			Knee	Ankle		
		Sagittal plane	Coronal plane	Horizontal plane	Sagittal plane	Sagittal plane	Coronal plane	Horizontal plane
RoM (L)	PD_SW	35.94±5.60	16.83±5.23	13.66±4.14	56.83±6.43	26.19±4.86	25.95±9.39	23.41±6.75
	PD_T	30.46±5.55	17.27±4.81	24.32±8.71	50.11±8.3	19.79±4.55	24.20±9.08	25.84±7.74
	HC_SW	41.78±4.72	14.70±3.29	19.27±6.75	62.60±4.77	30.19±7.85	19.07±7.20	19.03±6.02
	HC_T	36.21±5.17	14.92±3.24	37.51±4.71	57.90±4.92	22.35±6.13	18.81±5.58	23.23±6.46
	Group	***<0.001***	0.140	***<0.001***	***0.004***	0.150	***0.002***	0.144
	Task	***0.001***	0.377	***<0.001***	***<0.001***	***<0.001***	0.904	***<0.001***
	Interaction	0.786	0.773	***0.009***	0.149	0.987	0.653	0.166
RoM (R)	PD_SW	36.17±4.45	15.78±7.41	15.69±4.58	55.84±7.15	30.32±8.44	18.55±6.66	16.79±4.33
	PD_T	30.14±4.06	13.90±3.63	20.16±5.46	51.76±6.93	26.70±7.17	19.23±4.95	16.85±2.79
	HC_SW	41.99±4.66	13.24±3.79	17.02±6.34	64.34±4.10	32.25±6.44	14.45±3.56	19.96±8.58
	HC_T	33.35±3.62	13.25±2.17	34.67±6.63	59.79±4.01	26.62±4.3	17.46±3.05	19.53±5.32
	Group	***0.003***	0.412	***0.006***	***<0.001***	0.699	***0.026***	0.113
	Task	***<0.001***	0.707	***<0.001***	***<0.001***	***<0.001***	0.081	0.820
	Interaction	***0.009***	0.588	***0.026***	0.617	***0.049***	0.299	0.765
Variability of RoM (L)	PD_SW	0.64±0.3	0.53±0.35	1.01±0.83	0.76±0.42	0.95±0.44	1.47±0.75	1.45±0.81
	PD_T	1.92±0.76	0.90±0.40	2.90±2.03	2.23±0.93	2.41±1.26	2.54±1.19	2.56±1.28
	HC_SW	0.90±0.43	0.69±0.27	1.09±0.34	0.86±0.38	0.84±0.31	1.09±0.66	1.37±0.38
	HC_T	1.88±0.94	1.02±0.39	3.51±1.54	2.95±1.80	2.95±0.82	2.37±0.97	2.46±1.32
	Group	0.528	0.167	0.352	0.443	0.563	0.331	0.748
	Task	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***
	Interaction	0.358	0.788	0.406	0.996	0.266	0.565	0.974
Variability of RoM (R)	PD_SW	0.58±0.23	0.53±0.27	0.90±0.45	0.90±0.50	1.00±0.60	1.00±0.53	1.42±0.8
	PD_T	2.11±1.04	2.04±1.11	1.99±0.85	2.33±1.68	2.46±1.21	1.71±0.67	2.40±1.52
	HC_SW	0.68±0.28	0.70±0.31	1.26±0.42	0.83±0.22	0.98±0.55	0.92±0.49	1.84±0.61
	HC_T	2.05±0.78	1.28±0.64	3.38±0.86	1.87±1.00	2.25±0.88	1.72±0.84	3.28±1.48
	Group	0.902	0.109	***<0.001***	0.319	0.631	0.855	***0.014***
	Task	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***	***<0.001***
	Interaction	0.632	***0.008***	***0.003***	0.935	0.634	0.744	0.972
Asymmetry of RoM	PD_SW	14.92±19.48	30.44±22.46	23.85±11.95	7.21±6.89	19.41±15.73	80.47±114.02	58.79±51.54
	PD_T	16.82±13.44	35.88±22.32	36.70±26.38	10.65±6.41	31.90±18.10	61.58±73.44	61.05±45.56
	HC_SW	5.04±2.33	21.64±15.78	33.14±32.35	4.98±4.22	15.73±10.24	47.74±48.75	33.03±28.28
	HC_T	12.36±6.95	21.38±10.89	23.75±24.33	6.51±3.96	23.86±11.57	27.93±18.76	41.03±17.83
	Group	***0.047***	0.062	0.122	0.056	0.204	0.063	0.074
	Task	***0.003***	0.377	0.757	***0.010***	***<0.001***	0.159	0.197
	Interaction	0.072	0.330	0.050	0.600	0.377	0.194	0.501
Stability (L)	PD_SW	8.76±0.80	7.55±1.87	3.45±1.00	7.73±2.02	5.11±1.22	7.39±3.61	5.35±1.96
	PD_T	7.48±1.28	6.40±1.41	4.16±1.22	7.78±2.05	4.68±1.06	6.72±2.53	5.74±1.60
	HC_SW	9.03±1.38	7.05±1.33	5.36±2.25	8.10±3.16	5.98±1.65	5.11±1.12	6.19±2.36
	HC_T	7.48±0.75	6.09±0.93	5.63±0.76	7.72±1.42	5.37±1.45	5.93±1.05	5.41±0.83
	Group	0.767	0.364	***<0.001***	0.957	0.060	0.056	0.654
	Task	***<0.001***	***<0.001***	0.128	0.677	0.188	0.327	0.466
	Interaction	0.785	0.716	0.480	0.768	0.860	0.203	***0.038***
Stability (R)	PD_SW	8.90±1.35	6.92±1.92	3.40±1.06	6.58±1.13	5.69±1.76	5.43±2.57	4.39±1.41
	PD_T	7.38±1.06	5.31±1.54	3.87±1.11	6.36±1.78	4.92±1.73	4.04±1.18	4.33±1.42
	HC_SW	9.23±1.24	5.91±1.75	4.80±1.26	8.73±4.49	5.89±1.17	4.28±1.64	5.61±1.86
	HC_T	7.39±0.96	5.07±1.00	5.53±0.86	9.06±3.55	4.84±1.07	4.13±0.87	4.73±1.04
	Group	0.632	0.172	***<0.001***	***0.001***	0.545	0.451	0.078
	Task	***<0.001***	***0.002***	***0.031***	0.591	***0.010***	0.413	0.085
	Interaction	0.449	0.287	0.624	0.279	0.677	0.215	0.134

Significant differences ($p<0.05$) are indicated in bold and italics.

More joint kinematic parameters showed good sensitivity and specificity in the identification of early-stage PD. The AUC of RoM was greater than 0.67 in hip and knee flexion angle on both sides while the AUC of cervical flexion angle RoM was greater than 0.72 only during turning. PD exhibited discriminating neck and shoulder RoM in the coronal plane for both tasks (AUC>0.72) and in the horizontal plane only during turning (AUC>0.73). The RoM of hip rotation angle during turning showed the greatest AUC values (L: AUC = 0.89; R: AUC = 0.94) as shown in Fig.4(b).

The discriminating stability and variability parameters were mostly observed during turning as shown in Fig.4(c) and Fig.4(d). The AUC of shoulder stability in three dimensions was greater than 0.63 and showed the most discrimination in the horizontal plane (L: AUC = 0.76; R: AUC = 0.82). The stability of pelvis tilt angle obtained an AUC value over 0.68 on both sides and the AUC of right knee flexion angle stability was 0.647. The stability of hip rotation angle represented high sensitivity and specificity to identify early-stage PD patients from healthy elderly subjects in both straight walking and turning (AUC>0.77). The variability parameters did show good discriminating ability in most joints where only the AUC of cervical lateral angle RoM variability was greater than 0.7, Fig.4(d).

The discriminative gait parameters (AUC>0.7) shown in Table.V were categorized into 22 groups: respectively spa-

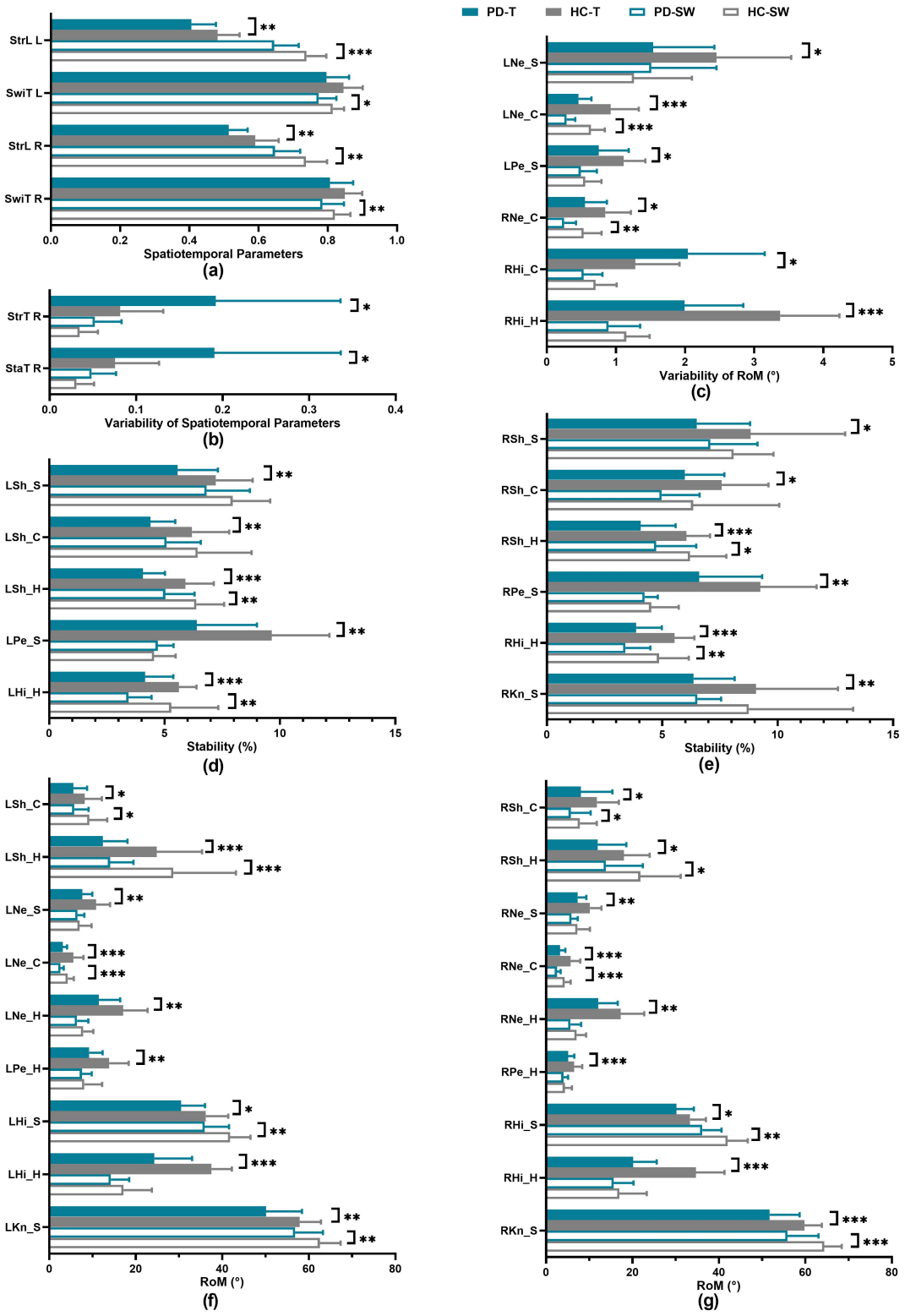

Fig. 3. Gait parameters comparison between PD and HC during straight walking(SW) and turning(T). Gait parameters that had a significant difference between PD and HC were plotted in this figure. Gait spatiotemporal related parameters were plotted in (a) and (b). Joint kinematics related parameters that variability, stability, and RoM of Neck (Ne), Shoulder (Sh), Pelvic (Pe), Hip (Hi), and Knee (Kn) in Sagittal plane (S), Coronal plane (C), and Horizontal plane (H) were plotted in (c), (d), (e), (f), and (g). * : $p<0.05$, ** : $p<0.01$, *** : $p<0.001$.

tiotemporal parameters, kinematics related parameters of individual joint (neck, should, pelvic, hip, and knee), all joints parameters, and all gait parameters under three conditions (straight walking only, turning only, and both gait tasks).

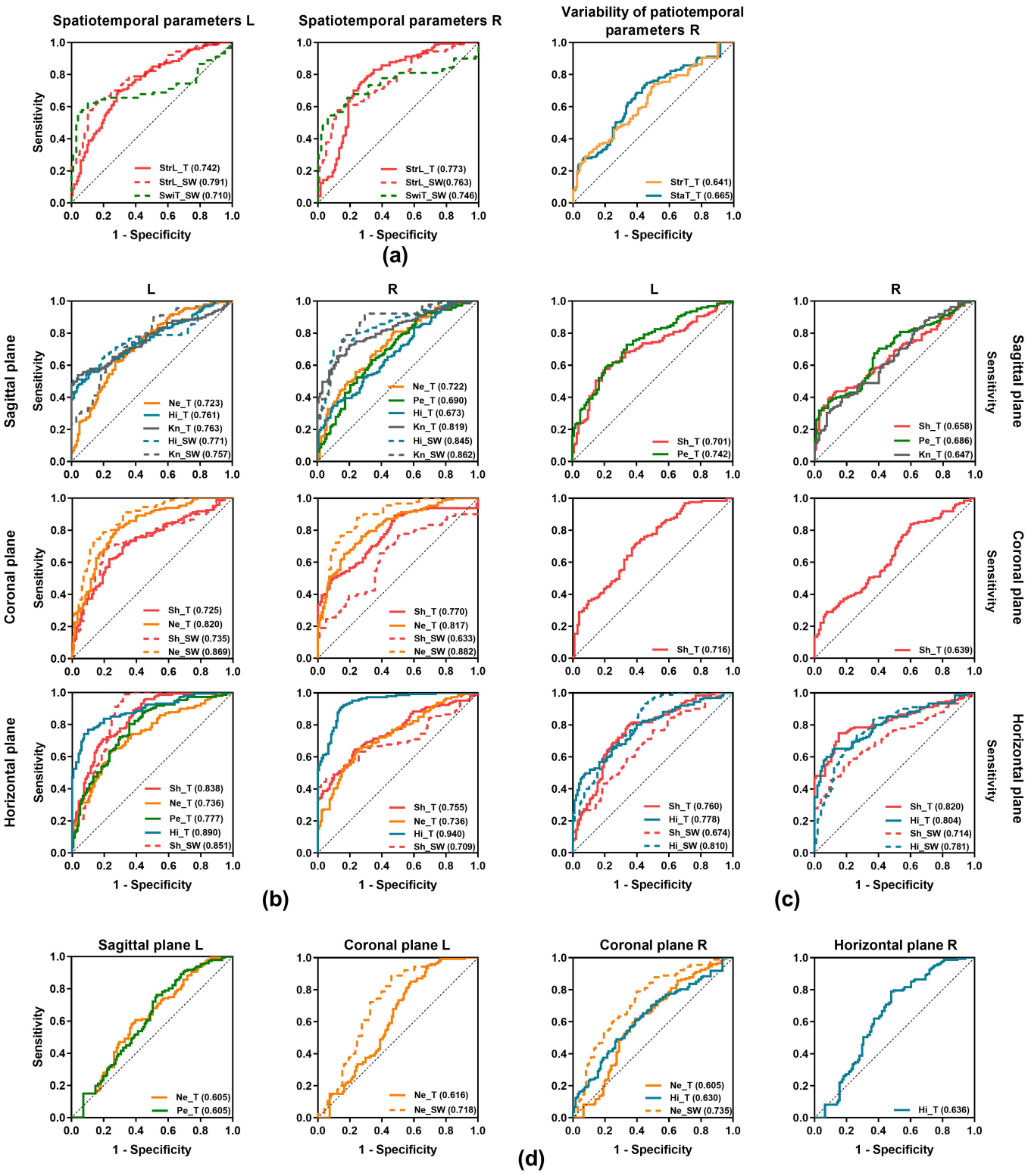

Fig. 4. The ROC curves of gait parameters that have good discriminating ability for PD and HC during straight walking (SW) and turning (T). (a) gait spatiotemporal related parameters; (b) joint kinematic parameters of RoM; (c) stability parameters; (d) joint variability parameters. The AUC of each ROC curve was shown within parenthesis.Ne, neck; Sh, shoulder; Pe, pelvic; Hi, hip; Kn, knee.

Fig.5 showed the comparison of classification accuracy when different gait parameters groups were used. The accuracy of spatiotemporal parameters and kinematics related parameters of neck and knee individual joint during turning was smaller than that during straight walking. Meanwhile, the accuracy of kinematics related parameters of shoulder, hip, and all joint

TABLE V
DISCRIMINATIVE GAIT FEATURES (AUC>0.7) FOR STRAIGHT WALKING AND TURNING.

Parameters types			Straight walking	Turning
Spatiotemporal parameters			Stride length Swing time (L) Swing time (R)	Stride length
Kinematics-related parameters of individual joint	Neck	RoM	Lateral	Flexion Lateral Axial
		Variability	Lateral	-
	Shoulder	RoM	Abduction (L) Rotation	Abduction Rotation
		Stability	Rotation (R)	Flexion (L) Abduction (L) Rotation
	Pelvic	RoM	-	Rotation (L) Tilt (L)
	Hip	RoM	Flexion	Flexion (L) Rotation
		Stability	Rotation	Rotation
	Knee	RoM	Flexion	Flexion

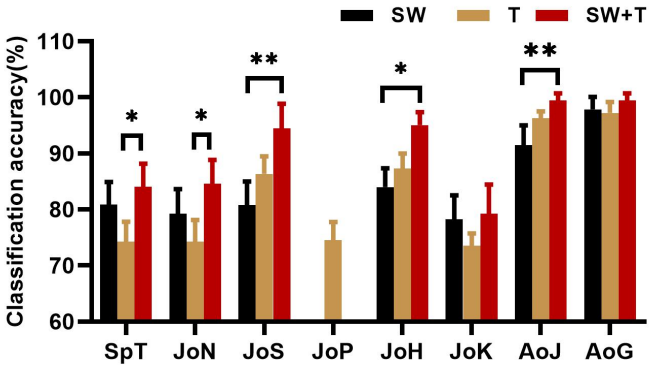

Fig. 5. Comparison of classification accuracy where different discriminative gait features groups were used. * : p<0.05, ** : p<0.01. SpT, spatiotemporal parameters; JoN, joint kinematics related parameters of neck; JoS, joint kinematics related parameters of shoulder; JoP, joint kinematics related parameters of pelvic; JoH, joint kinematics related parameters of hip; JoK, joint kinematics related parameters of knee; AoJ, all joints parameters; AoG, all gait parameters.

fusion features during turning was greater than that during straight walking. Although there was no statistical difference. Compared to the classification models based on single task, the accuracy was significantly improved fusing turning and straight walking gait features.

V. DISCUSSION

This paper proposed an inertial-based gait assessment model for both straight walking and turning. To the author's knowledge, the study was the first attempt to develop a gait assessment model to evaluate participants' gait performance during turning with quantitative and comprehensive parameters from five domains: gait spatiotemporal parameters, joint kinematics, variability, asymmetry, and stability. The model was employed to investigate discriminative gait metrics for early-stage PD. The results revealed that: 1) PD patients exhibited more obvious gait disorders during turning; 2) joint kinematics related parameters were more discriminative for identifying early-stage PD compared to gait spatiotemporal related parameters; 3) the fusion of gait features of straight walking and turning tasks can improve recognition accuracy of early-stage PD, which has potential to resolve conflicts between number of sensors and precision of disease diagnosis.

PD patients exhibited a various level of gait impairments in the five domains. Stride length was the spatiotemporal parameter PD with the most significant difference compared to the HC group, which reflects bradykinesia symptoms of early-stage PD patients [2], [27]. A study of Rehman et al. [28] presented that variability was the most discriminating gait feature (AUC 0.63-0.69) between the patients with early-stage PD (Hoen&Yahr 1) and HC. Fig.4(d) showed the variability of some joint RoMs (the neck, pelvis and hip) had the discriminative ability (AUC 0.60-0.735), the features had lower AUC values compared to those in other gait domains despite of cervical lateral angle. Wu et al. [29] demonstrated that PD patients at an early stage performed significantly reduced RoMs of knee and hip joints during straight walking, which was also observed in Fig.3. Moreover, we observed significantly reduced RoMs of neck angles (flexion, lateral and axial), shoulder angles (abduction and rotation) and hip rotation angle during turning (AUC 0.723-0.940). Fig.3 showed that patients exhibited more postural instability during turning compared to the HC group. The results of Rehaman et al. [28] and Serrao et al. [30] showed a significantly increased asymmetry in PD patients but we did not observe a significant difference between early-stage PD patients and HC in the asymmetry domain which was consistent with the results of Wu et al. [29]. The conflicting findings suggested that although asymmetrical degeneration of the basal ganglia in early-stage PD patients may lead to unilateral symptoms, measurement of gait variation between right and left sides may not be reliable to quantify patients' motor asymmetry.

PD patients at the early stage performed more severe gait impairments in joint kinematics during turning than straight walking. Several studies have assessed turning performance and related parameters employed as additional gait parameters for the walking performance [5], [21], [22], [31], [32]. Global features, such as turning time, step number, and turning speed were usually extracted. This study was the first attempt to present a novel inertial-based model that enables evaluation of gait performance at both straight walking and turning from five gait domains and investigated the discriminating ability of gait parameters for identifying early-stage PD. The results shown in Fig.3(f) and (g) revealed that PD patients had limited RoMs in the neck, pelvis, and hips during turning. The joint kinematics related parameters showed higher sensitivity and specificity for distinguishing PD and HC. The hip rotation angle at turns was the most discriminative feature for early-stage PD (L: AUC = 0.890; R: AUC = 0.940).

In this study, discriminative gait features were optimally screened with a threshold of AUC value larger than 0.7. The effect of optimized straight walking and turning gait features on early PD classification was compared with various IMU combination. Since all gait features were calculated based on our proposed spatiotemporal model, a body sensor network

consists of at least 5 sensors placed to the lower limbs where its classification accuracy under a single task ranges from 74% to 80%. The inclusion of joint kinematics related features may require more IMU sensors. The classification accuracy with individual joint parameters under straight walking task ranges from 78% to 84%, and that during turning ranges from 74% to 87%. The fusion of all discriminative gait metrics can achieve the highest accuracy of early PD recognition under either straight walking or turning (>97%), however, it relies on the largest body-sensor network (11 IMU sensors), which may be less practical in real clinical assessment environment. As shown in Fig.8, the fusion of gait features from both straight walking and turning tasks can significantly improve the recognition accuracy resulting in a good compensation of the insufficient information when using fewer sensors. The PD classification using the hip joint parameters under both tasks obtain a good accuracy (>95%) that is comparable to that using all parameters under a single gait task.

We observed that people with PD tended to a more conservative turning strategy. The PD group performed a reduced RoM of the hip and knee in the sagittal plan resulting in shorter stride length. The RoMs of neck flexion and rotation were significantly reduced during turning which may be due to their acquisition of visual information [33], showing that the different strategy of changing direction at turns was taken [34]. Limited rotation of the neck, pelvis, and hip was also observed at turns, which may be related to the axial rigidity in PD patients [3], [35]. The decreased RoM of lower-limb joint flexion and pelvis rotation demonstrated that the participants tend to reduce inter-segment rotation with shortened strides to avoid falls at 180 degrees turns.

There are some limitations in this study. Firstly, the number of patients was relatively small. Although the sample size was statistically reasonable to investigate gait performance between early PD and healthy control, a multi-center trial is necessary to further validate the proposed gait assessment model in a wider patient population. Secondly, the effect of the dopaminergic medications was not considered in this study. Previous study showed the dopaminergic treatment improved certain gait aspects, such as step duration, peak velocity during turning [36]. Gait characteristics of PD patients with medication ON and OFF conditions can be compared to clarify the influence of medication. Another limitation of our protocol is that only left-turning performance was investigated. Our results showed that early-stage PD group did not exhibit obvious asymmetric motor symptoms with medication ON, the direction of turning would not affect the findings in this study. However, it is worth to be explored the effect of turning strategy based on directions and its effects on PD walking performance in the further study.

VI. Conclusion

The present study developed a novel IMU-based gait assessment model to provide quantitative gait parameters during both straight walking and turning from five gait domains: spatiotemporal gait parameters, joint kinematics, variability, asymmetry, and stability. It was the first attempt to propose a comprehensive gait assessment of the turning performance of early-stage PD. Results revealed that patients with early-stage PD exhibited more gait abnormalities at turns mainly on the RoM and stability of the neck, shoulder, pelvic, and hip. These gait features have a better discriminating ability to identify early-stage PD patients. Furthermore, the inclusion of gait features at turns can help improve the classification accuracy and reduce the number of IMU sensors. These findings demonstrated that turning performance, especially joint kinematics related parameters, has great potential to be used for early-stage PD detection.

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