

An inertial sensor-based algorithm for turning detection during gait

Lin Meng¹, Xiayu Huang², Yifan Yang², Jun Pang¹, Lei Chen³, Dong Ming¹

Abstract—Patients with Parkinson’s disease (PD) can be divided into two subtypes based on clinical features, namely tremor-dominant (TD) and postural instability and gait difficulty (PIGD). Detection of PIGD symptoms is crucial for early diagnosis of PD and timely clinical intervention. However, patients at the early stage may not exhibit obvious motor dysfunctions during normal straight walking leading to difficulties in PD identification. Researchers have found that patients would show significant motor deteriorations in turning due to their cognition limitation. Therefore, turning detection is essential for quantitative motion analysis in the gait assessment of PD patients. In this study, we proposed a novel inertial-sensor-based algorithm for turning detection. Ten healthy young participants were enrolled in the experiment where they were required to walk along a 7-meter pathway with two 180 degree turns at their comfortable walking speed. Five inertial sensors were attached to the upper trunk, the shank and the foot of both legs. The algorithm performance was validated using an optical motion capture system for reference and two sensor combination options (upper trunk and shank sensors, upper trunk and foot sensors) were compared. The results showed that the proposed algorithm achieved accuracy over 98% for identifying the turning state of both legs. The integration of the upper trunk and foot sensors had no significant effect on the detection accuracy compared to that with the use of the upper trunk and shank sensors. Our algorithm has the potential to be implemented in the motion analysis model for complicated gait tasks, which has great potential in the early diagnosis of PIGD.

Keywords— gait; inertial sensors; turning detection; PD; PIGD

I. INTRODUCTION

Parkinson’s disease (PD) is the world’s second most common neurodegenerative disorder [1]. Patients are divided into two subtypes based on clinical features, namely tremor-dominant (TD) and postural instability and gait difficulty (PIGD). Compared to the TD subtype, PIGD patients have a worse prognosis and the disease may develop more rapidly [2]. Detection of early PIGD symptoms is crucial for early diagnosis of PD and timely clinical intervention. However, the PIGD symptoms in early PD are mild and may vary among different patients.

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Performance-based tests, such as Time Up and Go (TUG) test, assess patients’ mobility on transitions, gait and risk of falling. However, its clinical use is only timed scores that do not provide information about the pattern or quality of the motion, limiting its usefulness in assessing disease progression. It requires objective technologies to increase the accuracy of the assessment. Motion analysis technology provides an objective approach to measure subtle movement changes and quantitatively describe motor symptoms. Inertial measurement units (IMUs) have been widely accepted in gait assessment due to their portability, low cost and unconstrained environment requirement [3], [4]. Studies showed that PD patients may exhibit a reduced range of motion and muscle strength at the lower limbs resulting in reduced gait speed, step length [5], [6].

Mirelman et al. [7] demonstrated that PIGD patients exhibited gait slowness and abnormal postural adjustment which may happen at the early stage of disease, even before the appearance of gait disorder during walking. Dual-task and complex gait tasks may show promise for detecting patients’ abnormal motion functions compared to a straight walking task [8]. As a common gait task for daily life, turning is accomplished by a top-down sequence of body segment rotations requiring quick balance and posture adjustment []. Patients with PD exhibit poorer balance and impaired limb coordination during turning compared to walking which may result in a slower turning speed and wider turns [9]. Gait assessment of turning has drawn more attention in the field of PD motor dysfunctions [10]–[12]. However, to the authors’ knowledge, there is no existing motion analysis model that enables to quantify gait performance for both normal gait and turning tasks, in which, automatic turning detection is crucial for further data analysis.

In this study, we proposed a novel algorithm for turn detection based on inertial sensors. The two-layers model enables detection of the left and right turning using the course angle changes of body segment during gait cycles. The algorithm performance was evaluated in the experiment with optical reference. The effect of sensor fusion options (upper trunk and foot sensors, upper trunk and shank sensors) on the turning detection was investigated while the classification accuracy of left- and right-sided turning was compared. The rest of the paper was structured as below: The Section II detailed a two-layer model that comprises gait event detection and a rule-based machine learning approach with a fixed threshold for turning detection. The validation experiment and data analysis were described in the Section while results and conclusion were demonstrated in the Section III and IV.

II. METHODS

A two-layer model was developed based on a rule-based machine learning approach in this study. A gait event detection algorithm in the top layer determines the heel off (HO), heel strike (HS) events while the turning state can be characterized with the course angle changes of body segments between the HO and successive HS at the bottom layer of the model.

A. Gait event detection

The pitch angle θ_{pitch} measured from the sensor placed on the foot was used in our proposed gait event detection algorithm. The first-order differentiation of θ_{pitch} was calculated to obtain the angular velocity ω_{pitch} that was then filtered using a 3rd order zero-lag high-pass filter ($f_{HC} = 1Hz$). The foot pitch angle θ_{pitch} was filtered by a 12th order zero-lag low-pass Butterworth filter with a cut-off frequency of 5Hz. Three gait events were distinguished, namely the mid-swing (MSw), HO and HS. The MSw was determined as a reference time instant while the HO and HS were assumed to occur in a time window with a certain length before and after the MSw:

- MSw: the MSw was determined with the maximum point of foot angular velocity.
- HO: If a MSw was detected, the HO occurred at the moment when the local minimum point of the foot pitch angle within a 0.7-second time window before the MSw was found.
- HS: the HS occurred following the MSw when the foot pitch angle reached the local maximum within a 0.5-second time window.

B. Turning state detection

Fig. 1 shows the course angles of sensors that were placed on the upper body, the left shank and the left foot of one participant when he performed straight walking followed by 180 degree turns in 5 seconds. It can be observed that a significant change in the course angles occurs during the turning. The change of course angles between the HO and next HS events are calculated based on gait phase detection:

$$\Delta \theta_i = \theta_{i,HO} - \theta_{i,HS} \quad (1)$$

Where i represents the foot, shank and upper trunk sensors respectively. Two sensor combination options are proposed where the upper trunk sensor is integrated with the foot or shank sensor (the upper trunk and shank sensors, the upper trunk and foot sensors). The gait stride is regarded as a turn if:

$$|\Delta \theta_{UT}| > 20 \text{ and } |\Delta \theta_{FO/HS}| > 15. \quad (2)$$

C. Experimental protocol

The study was approved by the Ethics Committee of Tianjin University and was conducted in the Motion Rehabilitation Laboratory of Tianjin University. Ten healthy young participants (5 males and 5 females, age 23.00 ± 0.82 years old, weight 60.71 ± 11.25 kg, height 168.00 ± 9.40 cm) were

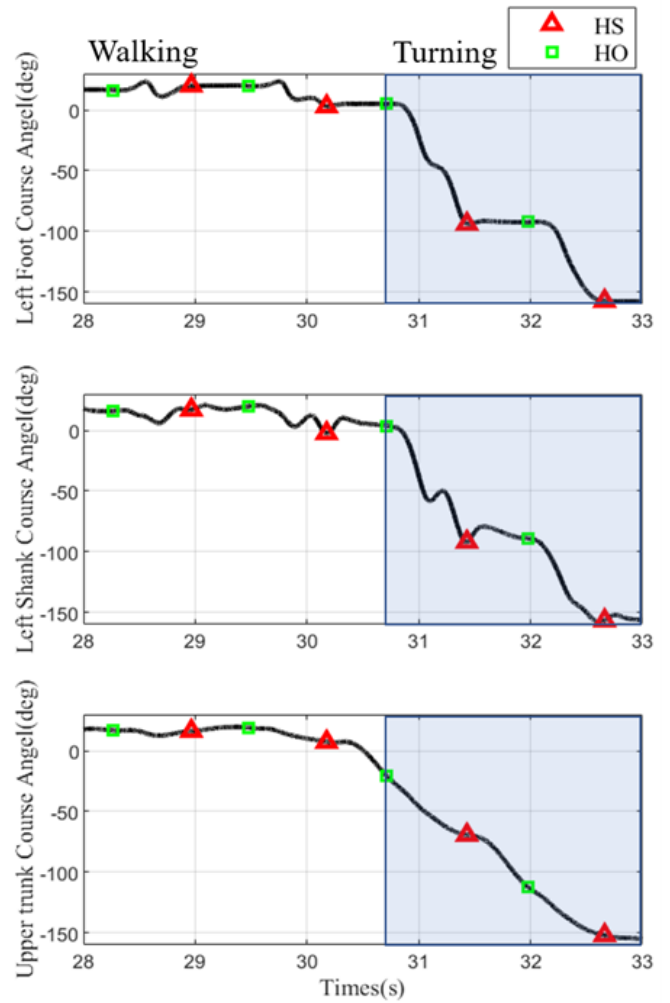


Fig. 1. The course angles of sensors placed on the upper body, the left shank and the left foot of one participant when performing the straight walking followed by 180 degree turning within 5 seconds. The heel strike (HS) and heel off (HO) events were detected and marked in the plots.

enrolled in the experiment. All participants provided written informed consent prior to the experiment.

As shown in Fig. 2A, a participant wore five inertial sensors (myOMOTION™, Noraxon, US) that were placed at the upper trunk, shank and foot respectively. The upper trunk sensor was attached at the level of the third lumbar vertebra in order to closely match the centre of mass movement during gait. The shank sensor was placed at the inner side of the tibia 10cm below the knee bilaterally for minimizing relative artificial movement between the skin and the bone. The foot sensor was placed at the 3rd metatarsal of the foot. The Vicon optical motion capture system (Vicon MX Giganet, Oxford Metrics Ltd., UK) was used as the reference for algorithm validation. The straight walking and turning tasks were segmented using the marker trajectories of the heel and toe. A static trial was firstly captured while the participant standing still with a natural posture. Then, the participant was required to perform a complex gait task comprising of straight walking and 180 degree turning as shown in

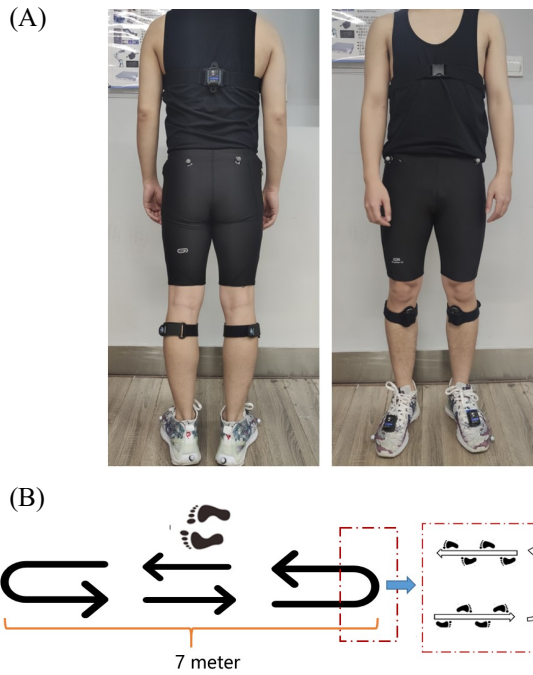


Fig. 2. (A) The participant wore five inertial sensors placed on the upper trunk, shank and foot of both legs while the retroreflective markers were placed on the heel and toe for identifying the straight walking and turning as the reference. (B) The participant was required to walk along the 7-meter pathway with two 180 degree turns for 20 cycles.

Fig. 2B along a 7-meter path at his/her comfortable speed and completed 20 cycles. The inertial data and marker trajectories were collected synchronously at a sampling rate of 100Hz.

D. Data analysis

The proposed algorithm was programmed using MATLAB2019b (The MathWorks, Inc., Natick, MA, US). A total of 1193 gait strides on the left side and 1107 gait strides on the right side were extracted. The accuracy of gait event detection was evaluated firstly based on which the gait strides were classified into two gait tasks: straight walking and turning. The algorithm performance using the two sensor fusion options were evaluated in terms of sensitivity, specificity and accuracy and compared with the use of the Student's t-test. A p-value less than 0.05 was considered statistically significant.

III. RESULTS

The Vicon system was used as a reference system to verify gait events (HS and HO) and gait tasks (straight walking and turning). The gait phase detection algorithm obtained an accuracy of 100% to identify the HS and HO events for all participants' trials. As shown in TABLE I, the average time difference between the detected gait phases and Vicon reference were less than 5ms for the HO and 30ms for the HS.

The algorithm performance of the turning detection based on two sensor fusion strategies was analyzed. It should be noted that turning states were detected for the left and right legs respectively in this study. For an instant, the course

TABLE I
RESULTS OF TIME DIFFERENCE BETWEEN THE DETECTED GAIT PHASES AND VICON REFERENCE

Leg side	HO (ms)	HS (ms)
Left	4.73 ± 14.06	29.86 ± 23.32
Right	0.04 ± 16.34	14.94 ± 30.07

angles of sensors placed on the upper trunk and left foot (or shank) were used for determining the left turning state. As shown in Fig 3 and TABLE II, our proposed algorithm obtained a good accuracy for turning detection ($> 97\%$) based on both sensor fusion methods. The sensor fusion strategy had no significant effect on the classification performance. However, we observed that the turning detection performance was slightly worsened on the right side ($> 98.25\%$) compared to that on the left side ($> 99.40\%$). There was a significant difference in the classification accuracy of the right and left side turning ($p < 0.05$). This may be because all participants performed only left 180 degree turnings in the experiment. As the outer leg, the right leg exhibited higher gait kinematics variability during gait so that more right-turning states were misclassified as right walking (Fig 3).

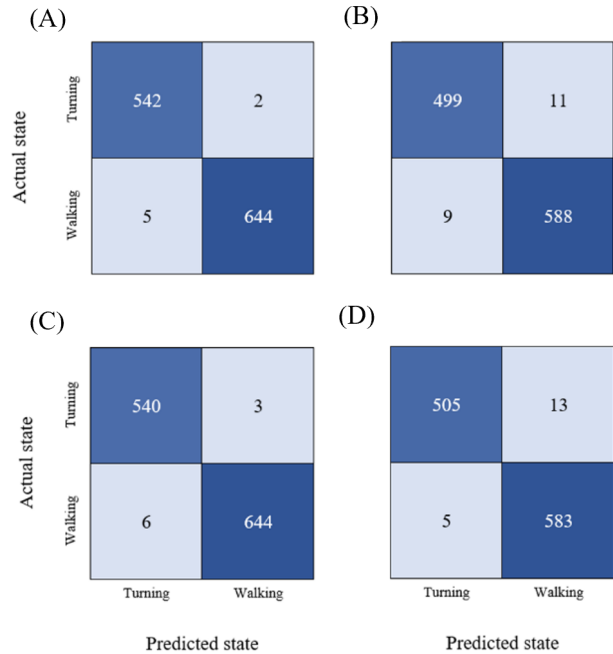


Fig. 3. Recognition confusion matrix of straight walking and turning respectively on the left and right side with the use of two sensor combination strategies: (A) Upper trunk and left foot sensors; (B) Upper trunk and right foot sensors; (C) Upper trunk and left shank sensors; (D) Upper trunk and right shank sensors.

IV. DISCUSSION AND CONCLUSION

In this paper, we proposed a novel two-layer model that enables to detect the turning during gait. The concept

TABLE II

CLASSIFICATION PERFORMANCE ON DETECTION OF LEFT AND RIGHT TURNING STATES BASED ON TWO SENSOR FUSION STRATEGIES

Leg Side	Sensor fusion strategy	Sensitivity	Specificity	Accuracy
Left	Upper Trunk and foot sensors	99.67 ± 0.88	99.14 ± 0.64	99.40 ± 0.55
	Upper Trunk and shank sensors	99.41 ± 1.02	99.08 ± 0.98	99.47 ± 0.45
Right	Upper Trunk and foot sensors	97.96 ± 1.85	98.49 ± 2.06	98.25 ± 1.71
	Upper Trunk and shank sensors	97.66 ± 2.33	99.10 ± 1.14	98.43 ± 1.35

of the algorithm is to distinguish the turning state if the course angle changes of sensors placed on the upper trunk and foot (or shank) exceed the set-up threshold values. The gait phase detection algorithm can identify the HO and HS events during both straight walking and turning tasks with an accuracy of 100%. The course angle change between the HO and successive HS events was calculated and used in the rule-based machine learning approach of which performance was evaluated in the experiment. Results showed that the approach obtained a good performance on the turning detection with accuracy over 98%. The choice of sensor location (foot or shank) does not have a significant effect on the classification accuracy. However, the turning direction may affect the accuracy of turning identification due to the kinematic difference of the inner and outer leg during turning.

The results suggested that it is feasible to achieve a plausible classification performance on straight walking and turning with the use of three sensors, e.g., one placed on the upper trunk and two on both feet respectively. As inertial sensors are lightweight and small in size, they will not hinder the gait pattern of PD patients. A limitation of this study is that the algorithm has not been validated on patients. The PIGD patients are now enrolled in our ongoing study for clinical validation. Moreover, the turning detection algorithm will be further implemented in a motion analysis model for complex gait tasks in which gait variables can be estimated for patients with motion dysfunctions in near future.

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