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Quantitative Analysis of the Gait Variability and Asymmetry Using Inertial Measurement Unit During Dual-task Gait

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***Abstract*—Well-established connections exist between increased gait variability and greater fall likelihood in human movement. Therefore, the assessment of gait symmetry can facilitate clinicians' decision-making in the treatment and evaluation of the progression of several diseases. This study proposed a workflow that used two self-developed inertial sensing measurement units (IMU) to collect the lower limb gait data of five subjects and then extracted the gait characteristic parameters to quantify the running process during a single-task condition and a dual-task condition, which requires additional cognitive loads (counting numbers backward). The results showed that the absolute value of the symmetry index under dual-task conditions (0.207±0.032) was greater than that of single-task conditions (0.149±0.109). The variability indices of the legs were reduced and the outliers of the asymmetry indices were significantly higher in the dual-task gait. This study revealed changes in gait symmetry and variability under dual-task gait conditions and found that human gait improved under dual-task conditions at high speeds, which can be instructive for gait quality improvement. In the future, the experimental conditions will be extended to include single-gait mode as well as walk-run and run-walk cross-gait modes to further validate the relationship between dual-task conditions and changes in gait characteristics.**

Keywords—Dual-task running, Gait index, Two IMUs, Gait event, Asymmetry index

I. Introduction

Running is considered to be an acquired rhythmic motor behavior that needs to be achieved through the integration of multiple sensory information. During high-speed running, the human body needs to focus more attention on maintaining gait balance [1]. Dual-tasking refers to the act of carrying out two attention-demanding tasks at the same time, each with a different objective [2]. In real life, multiple parallel tasks often occur. In dual-task gait, gait is the main task, and the secondary tasks are Serial subtraction, Word chain, Stroop task, and other tasks with a certain cognitive load [3]. Dual-task gait analysis can reveal difficulties in performing multitasking in patients with some neurodegenerative diseases (e.g., Parkinson's disease, mild cognitive impairment) or brain injuries, and can help in early diagnosis and monitoring of disease progression [4], [5], [6]. Due to an attentional competition mechanism between dual tasks, this is manifested in gait characteristics that differ somewhat from those of single-task gaits. The difference can be quantified by calculating the gait parameters separately for single and dual tasks.

Currently, people tend to use flexible, efficient, and cheap wearable inertial sensors as tools to perform gait analysis [7]. A foot-worn IMU was used to evaluate the gait parameters of healthy participants under single-task and dual-task conditions, and the reliability of the assessment by the foot-worn IMU was verified [8].

For the calculation of gait parameters, Wang developed a new IMU-based method for clinical gait assessment [9]. Nine gait variables, including three spatio-temporal and six kinematic parameters, were extracted by wearing IMUs on the shanks of both feet. Trupti extracted events occurring during walking using two MPU6050 sensors placed on the calves of both legs [10]. Zhang developed a wearable IMS module to be carried on the back of one foot, where a spatio-temporal gait analysis algorithm was developed to automatically acquire spatiot-emporal gait parameters using acceleration and angular velocity signals [11]. Yonatan proposed a framework for quantitative gait assessment using only two Inertial Measurement Unit (IMU) sensors, which successfully extracted 17 gait features from two IMUs located on the foot [12]. These studies have shown that sufficient gait parameters can already be extracted using two IMUs worn on both feet or a bipedal shank, and the accuracy of the gait parameter calculations can be verified by gold standards such as optical motion capture systems and force table systems [13]; In terms of research on the differences between single and dual tasks through gait parameters, Hutabarat concluded that subjects in dual-task gait decreased in exercise intensity and increased in double-support time [14]. Chorong conducted experiments using a GAITRite© walkway and found that at higher cognitive loads, the participants' Functional Walking Profiles (FAPs), speed, and stride length decreased and double support time increased [15]. Chiarello found that step length and speed decreased and step time increased with increasing cognitive load [16].

As research continues, our understanding of dual-tasking has deepened. However, key gait parameters in dual-task scenarios, such as gait asymmetry and gait variability, have yet to be fully explored. In addition, most studies have analyzed normal walking patterns, lacking analysis of running patterns since dual-task gait treadmill training was more effective in improving gait ability in dual-task training [17]. To address the above limitations, in this paper, we adopted the self-developed IMU device to wear on the left and right feet for the calculation of gait spatio-temporal parameters and gait indexes and verified its accuracy by the optical capture system. Aiming at a special state like dual-task running which can affect gait characteristics, the differences in Symmetry index, Asymmetry indices, and Variability indices under single and dual-task conditions were investigated [12].

II. Experiment Design and Data Collection

A. Participants

In this study, five subjects were recruited to participate in the study (age = 26.0 ± 6.245 years, height = 171.6 ± 9.016 cm, weight = 65.2 ± 10.473 kg), and all five subjects are healthy adults. Before the experiment, all subjects signed an informed consent form. This study has previously been approved by the Ethics Committee of Shenzhen Institutes of Advanced Technology [SIAT-IRB-230915-H0671]. All experimental operations were completed by experimental operators.

B. Experimental Setup

In this experiment, we used a self-developed wireless inertial sensor network to acquire gait parameters. The system consisted of a host computer, a base station, and two nodes (shown in Fig. 1). Only two nodes were used in this study, which are tied to the insteps of the left and right feet respectively, and each node included a three-axis acceleration, a three-axis gyroscope, and a magnetometer. The data from multiple nodes can be transmitted to the base station synchronously through the 2.4G radio-frequency technology (the system adopts a 1-to-many star-type wireless network), which in turn transmits the data to the host computer. The system provides a low-power and convenient platform for the real-time acquisition of multi-inertial data for this experiment.

In the system, we used Nordic's 2.4G wireless transceiver and signal processing as a whole nrf52832 for wireless communication, and TDK's icm42605 as a low-power inertial sensing unit. The collected signals are transmitted to the remote base station and then connected to the host through USB to serial port. Finally, the host computer receives the three-axis acceleration, angular velocity, and original parameters of the magnetometer from the remote inertial sensor. Two inertial sensing nodes are worn on the left and right feet, and self-adhesive elastic bandages are used for adhesion. 16 reflective markers for the motion capture system (Vicon nexus 2.12.1, UK) are placed at specific locations on the subject's pelvis and lower limbs.

C. Data Acquisition

At the start of each trial, the participant stood on a force platform (AMTI) for 6 seconds to calibrate and then jumped vertically to synchronize the motion sensors with the motion capture system. 12 optical cameras were used to capture the position of reflective markers at a sampling frequency of 100 Hz. The connectivity maps of the human lower limb skeletal system were obtained through calibration on the Nexus 2.12.1 software on the host computer. In addition, two nodes with inertial sensing on the left and right feet obtained three-axis acceleration, angular velocity, and magnetism at a sampling frequency of 100 Hz. All five subjects completed a single-task experiment and a dual-task experiment, respectively.

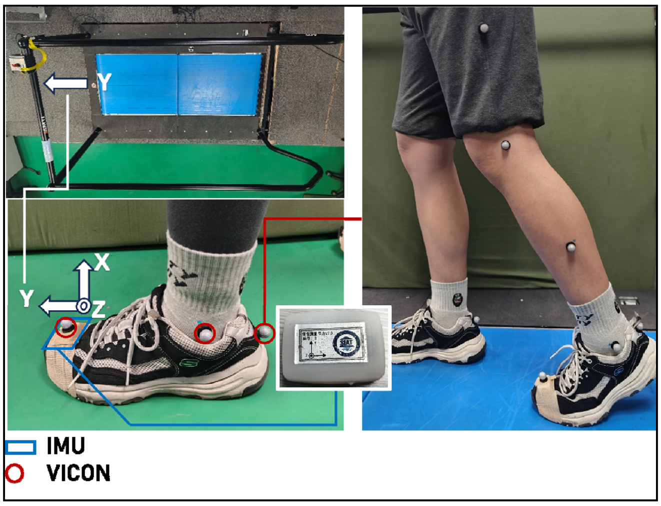

Fig 1. Subjects wore inertial sensing nodes and reflective markers, completed the communication connection between the inertial sensing nodes and the host computer, and calibrated reflective markers on the running platform.

1) Single-task experiment: The subject stood on the running platform, and the running platform accelerated from 0 to the specified speed of 8 km/h. Simultaneous remote IMU and Vicon data acquisition began when speeds reached 8 km/h. when the speed reached 8 km/h. During the test, the individual was required to concentrate on their running pace and maintain a constant speed of 8 kilometers/hour for 100s. After the test, the subject should take a 3-minute break to reduce the impact of fatigue.

2) Dual-task experiment: To simulate real-life situations that demand cognitive burden and physical exertion, subjects were instructed to engage in a continuous countdown from 500 while subtracting 2 from each number and vocalizing the results [3]. This exercise aimed to heighten their cognitive strain and sustain their focus and lasted for 100s. All other experimental parameters and data-gathering techniques remained consistent with those applied in single-task experiments.

III. METHOD

A. Preprocessing

After obtaining the initial acceleration and angular velocity of the inertial sensors, we performed the estimation of three main gait events, namely Initial Contact, Toe-Off, and Mid-Swing. Initial contact, also known as heel strike (HS), is the moment when the heel first touches the ground. Through Fig. 2, we first found the mid-swing state based on the maximum value of angular velocity in the counterclockwise direction. We constructed the over-zero detection algorithm to detect the HS of the initial contact [18]. Then we found the next maximum value of Toe-Off (TO) from this mid-swing state to the next mid-swing state [19]. Of these gait events, MS and TO are defined as local maxima, while HS is defined as the cross position where the threshold is zero. These descriptions are explained in Equations (1) to (8), where the subscripts i, L, and R are the index of the detected event, left and right, respectively.

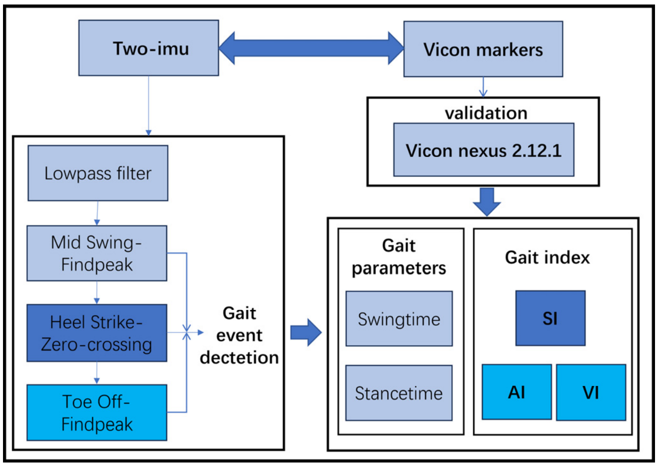

Fig. 2 Principles of gait parameter calculation and validation

B. Gait Parameters

$$\text{stride time} = IC_{i+1} - IC_i \tag{1}$$

$$\text{stance time} = TO_i - IC_i \tag{2}$$

$$\text{swing time} = IC_{i+1} - TO_i \tag{3}$$

$$\text{swing cycle} = \frac{\text{swing time}}{\text{swing time} + \text{stance time}} \tag{4}$$

$$\text{stance cycle} = \frac{\text{stance time}}{\text{swing time} + \text{stance time}} \tag{5}$$

In this paper, detailed temporal features were computed using two IMU sensors. From detecting the left IC, the right TO to the middle swing MS, we derived gait spatio-temporal parameters and gait indices based on the extracted temporal gait features.

The gait spatio-temporal parameters consist of stride time, swing time, and stance time, which are defined by gait events. The gait time is the period from the initial contact moment in the current gait cycle to the initial contact in the next gait cycle, and the swing time is the period from the initial contact in the current gait cycle to the toe-off in the next gait cycle, and the stance time is the period from the initial contact to the toe-off in a gait cycle.

The gait index includes:

1): Symmetry index (SI): a feature derived from the standing time of the left and right feet. To calculate this feature, we averaged the total stance time of the left and right feet for each running gait cycle in the experiment. Using the ratio of the total stance time of the left foot to the total stance time of the right foot minus 1 as a reference, a negative result of the calculation indicates a shorter overall standing time of the left foot, and a positive result indicates a shorter overall stance time of the right foot. The smaller the absolute value of the value indicates a higher symmetry between the left and right feet.

2) Asymmetry indices (AI): the difference between the mean values of the left and right feet at the same gait time and then taken as an absolute value, the gait time can be either the stance time or the swing time, the larger the value the higher the asymmetry.

3) Variability indices (VI): derived from the standard deviation of the gait time, which can be stance time or swing time. The variability index shows the difference in the movement state at different times during running, which can reflect the stability of the movement state.

The formulae for SI, AI, and VI are as follows, where f stands for swing time or instance time, and n represents the number of detected gait cycles：

$$\text{SI} = \sum_{i=0}^{n} \frac{\text{stance time}_L}{\text{stance time}_R} - 1 \tag{6}$$

$$AI_f = \text{Abs}\left(f_L - f_R\right) \tag{7}$$

$$\text{VI} = \text{S.D}\left(f\right) \tag{8}$$

C. Statistical Analysis

This study used Scatterplot and Bland-Altman plots to verify the consistency of gait event detection using the over-zero detection algorithm and Vicon respectively. Pearson's coefficient was utilized to conduct correlation analysis on gait phases during both single-task and dual-task conditions, with significance being tested using a two-tailed t-test ($\alpha < 0.05$). The radar chart presents the difference in gait index between single-task and dual-task conditions, while the box plot reflects the distribution range changes of AI under the same conditions.

IV. RESULT

A. Gait Event Validation

The proposed algorithm and the Vicon were used to calculate the coefficients of determination R2 between the four gait event timestamps, which are found to be 0.999 (Fig. 3A), 0.999 (B), 0.988 (C), and 0.996 (D). Table Ⅰ displays the mean and standard deviation of gait event for the proposed method and Vicon comparison. The Bland-Altman plots in Fig. 3 display the agreement between the proposed method and Vicon.

Table I. Difference between the results of the proposed method and Vicon system.

Gait Phase	IMU-Vicon	
	Mean	**SD**
HS (L) [s]	**0.412**	**1.051**
HS (R) [s]	**0.255**	**2.239**
TO (L) [s]	**10.771**	**6.286**
TO (R) [s]	**10.933**	**7.716**

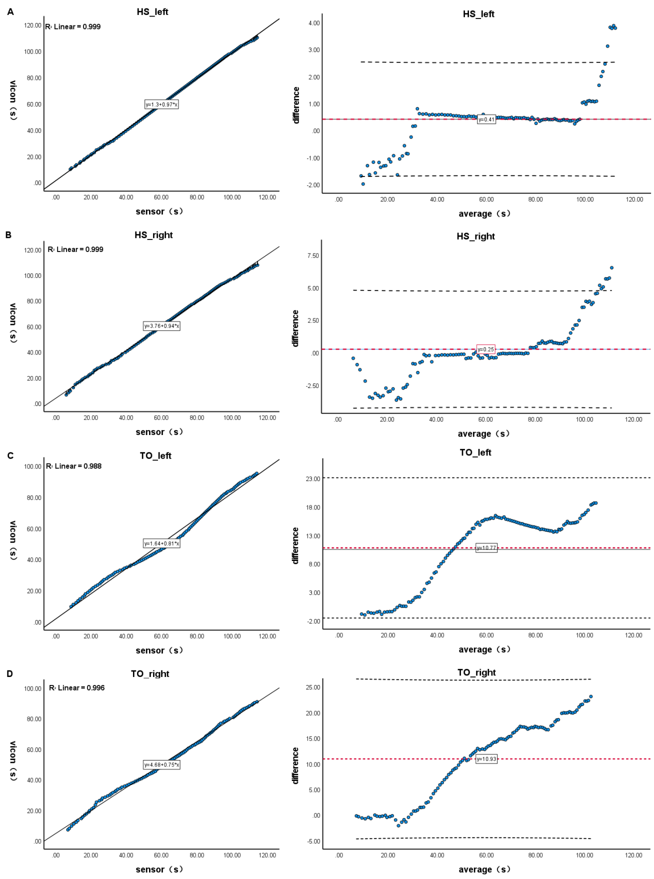

Fig. 3 Comparison of the proposed method with the Vicon standard. Scatterplots and Bland-Altman plots for (A) left HeelStrike, (B) right HeelStrike, (C) left ToeOff, and (D) right ToeOff.

B. Gait Phase Analysis

Table II shows the difference in gait phase between single-task and dual-task when running at 8 km/h. SO1-SO5 represents five experimental subjects in turn. Under single-task conditions, the p-values of five subjects are all less than 0.01, and the Pearson correlation coefficients are all negative, ranging from -0.30 to -0.57; Under the dual-task condition, the p-value was less than 0.05 for SO1, SO5, and less than 0.01 for SO2, SO3, SO4. Pearson correlation coefficients are also all negative, ranging from -0.20 to -0.70. In Fig. 4 (A), the gait cycles of SO1, SO2, and SO3 decreased under dual-task conditions, and the phase ratio of swing time and stance time fluctuated between 0.45-0.70.

C. Key Gait Index Measure

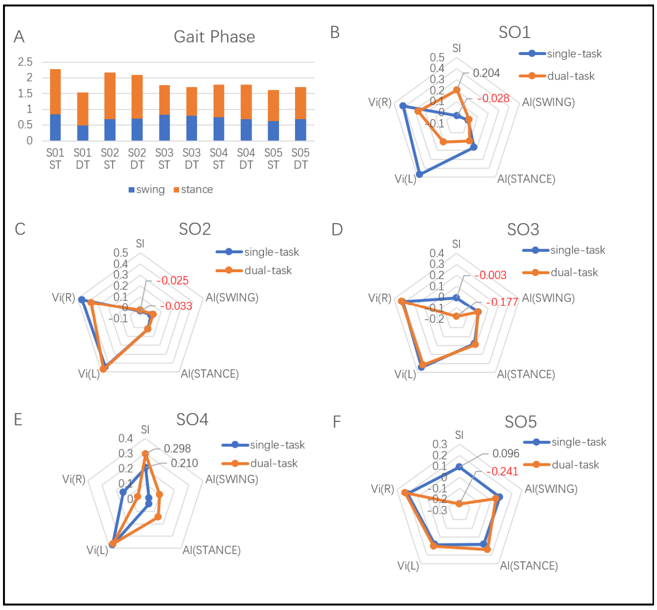

Fig. 4 (A) Standing phase swing phase ratio of five subjects, ST represents single-task, DT represents dual-task. (B)(C)(D)(E)(F) represent the characteristic distributions of gait asymmetry from single-task to dual-task.

Fig. 4 shows the difference in gait index between single-task and dual-task at 8 km/h. Through Fig. 4 (B), SO1 has a higher symmetry value level in dual-task gait. The AIs for swing time and standing time for the dual-task gait are 0.020 and 0.096, converging to 0, and the VIs for the left and right legs are 0.108 and 0.267, whereas the values are 0.473 and 0.414 for the single-task gait. Under dual-task condition, the SI of SO1 is 0.204, indicating poor gait asymmetry compared to 0.028 under single-task condition; according to Fig. 4 (D)(F), SO3 and SO5 have similar symmetry value levels in single and dual tasks. However, the absolute value of SI for SO3 dual-task gait (0.177) is greater than that of single-task gait (0.003), and the absolute value of SI for SO5 dual-task gait (0.241) is greater than that of single-task gait (0.096). The gait symmetry performance of all three subjects is better under single-task conditions, despite their symmetry value levels changing differently under dual-task gait. According to Fig. 4 (C)(D)(F), the VI of these three subjects under single and double tasks is basically identical. In Fig. 4(B)(E), the two subjects, SO1 and SO4 show a significant decrease in VI during dual-task conditions.

Through Fig. 5, SO1 and SO4 have the same mean values of AI in DSWING and DSTANCE, respectively, and both have extreme outliers, and the range of parameter fluctuation in single-task is larger than that in dual-task; SO2 has extreme outliers in AI in DSWING, and the range of parameter fluctuation in the stance phase is larger than that in the swing phase; SO3 has a consistent data distribution in SSWING, SSTANCE, DSWING, and DSTANCE. However, in the dual-task condition, the median line shifts upward, indicating a

Table Ⅱ. Analysis of Gait Phase Correlation under Single-Task and Dual-Task at 8KM/h

Subject	**Single-task** (Mean ± Standard Deviation)				**Dual-task** (Mean ± Standard Deviation)			
	Swing time (s)	Stance time (s)	r	P1	Swing time (s)	Stance time (s)	r	P2
SO1	0.84±0.29	1.44±0.34	**-0.36****	**<0.01****	0.49±0.10	1.04±0.18	**0.20****	**0.029***
SO2	0.68±0.28	1.49±0.34	**-0.57*****	**<0.01****	0.70±0.23	1.39±0.36	**-0.70******	**<0.01****
SO3	0.82±0.24	0.95±0.24	**-0.52*****	**<0.01****	0.80±0.22	0.91±0.25	**-0.52*****	**<0.01****
SO4	0.75±0.21	1.04±0.21	**-0.51*****	**<0.01****	0.68±0.20	1.11±0.17	**-0.44*****	**<0.01****
SO5	0.62±0.12	1.00±0.10	**-0.30****	**0.001*****	0.69±0.10	1.01±0.14	**-0.22****	**0.019***

Pearson Correlation test; Key: *|r|<0.2; 0.2<**|r|<0.4; 0.4<***|r|<0.6; 0.6<****|r|<0.8. Results are found to provide a significant correlation between the two conditions. Two-tailed T-test; Key: *p<0.05; **p<0.01; ***p<0.001. Results in bold are found to provide significant discrimination between the two conditions.

systematic change in the mean value of the parameter compared to the single task.

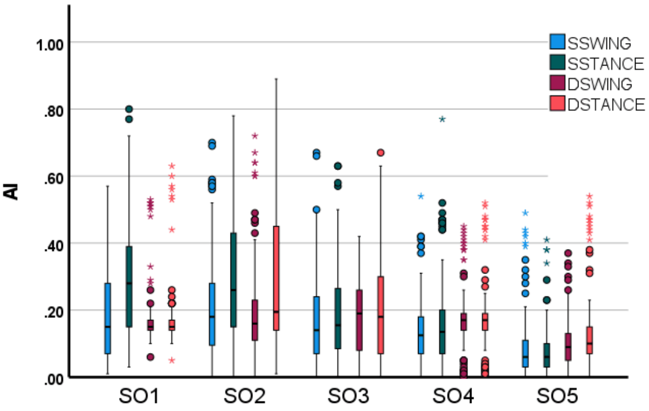

Fig. 5 Distribution of AI in swing time and stance time from single-task state to dual-task state. SSWING, SSTANCE, DSWING, and DSTANCE respectively denote the single-task swing phase, single-task stance phase, dual-task swing phase, and dual-task stance phase. Extreme outliers are shown as asterisks and moderate outliers are shown as dots.

V. Discussion

The Vicon validation results suggested that the foot localization IMU system is considered a simple and reliable method to measure gait events [20], which is accurately classified by the over-zero detection algorithm and further calculated to obtain a series of gait parameters.

The results of the gait phase analysis showed that there was a significant correlation between stance time and swing time under different cognitive load conditions, validating the consistency of the measurements under single and dual tasks. As the Pearson Correlation (r) was less than 0 for the five subjects, standing time and swing time are negatively correlated overall. There is individual variability in the phase ratios of standing time and swing time during a gait cycle, which might increase or decrease in the dual-task condition compared to the single-task condition, fluctuating between 0.47 and 0.87.

By analyzing the key gait indexes of the five subjects, we observed the absolute value of SI in single-task gait is less than that in dual-task gait for all five subjects, indicating better gait symmetry performance under single-task conditions. Regarding the asymmetry index, while the participants SO1, SO2, and SO3 displayed similar levels of AI during both single and dual-task conditions, it is worth noting that the AI outliers experienced a significant increase during the dual-task scenario in Fig. 5, suggesting a greater degree of asymmetry while simultaneously performing multiple tasks. Some subjects (SO1, SO2, SO4) had significantly lower VIs and smoother gaits while performing the dual task, while the remaining two subjects (SO3, SO5) had no significant change in VI, suggesting that the dual task has the potential to improve average gait quality.

We acknowledge some limitations of the study. First, the proposed method is suitable for gait analysis, but there is room for improvement in its accuracy, and further development of this IMU-based gait analysis method will enable us to use such systems for clinical gait analysis. In addition, this study only explored the characteristic distributions of gait parameters in the running gait mode and did not compare them with those in the walking gait mode, but the results of dual-task gait analysis in the walking gait mode can be found by referring to [14]. In addition, the problem of cognitive load and its impairment of gait increases with age while only five subjects were recruited for this experiment and all were healthy adults. We recently recruited 25 older adults from the community, five of whom had Parkinson's disease. We will further validate the relationship between the dual-task condition and gait characteristic changes, and extend the experimental conditions to walking gait patterns as well as walking-running and running-walking cross-gait patterns.

VI. Conclusion

This paper verified the reliability of gait parameter assessment under the running condition based on the self-developed inertial measurement unit and the quantitative analysis method of gait asymmetry. All participants exhibited worse gait symmetry, had significantly higher outliers in AI, and greater absolute values of SI in dual-task gait compared to single-task gait. In addition, in the dual-task condition, subjects' gait VI values were reduced or remained unchanged, indicating the potential benefits of dual-task training in improving gait quality.

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REFERENCES

[1] Soulard J, Vaillant J, Balaguier R, et al. Spatio-temporal gait parameters obtained from foot-worn inertial sensors are reliable in healthy adults in single- and dual-task conditions[J]. Scientific Reports, 2021, 11(1): 10229.

[2] Beauchet O, Berrut G (2006) Gait and dual-task: definition, interest, and perspectives in the elderly. Psychol Neuropsychiatr Vieil 4:215–225

[3] Baek C Y, Chang W N, Park B Y, et al. Effects of dual-task gait treadmill training on gait ability, dual-task interference, and fall efficacy in people with stroke: A Randomized Controlled Trial[J]. Physical therapy, 2021, 101(6): pzab067.

[4] Wollesen B, Rudnik S, Gulberti A, et al. A feasibility study of dual-task strategy training to improve gait performance in patients with Parkinson's disease[J]. Scientific Reports, 2021, 11(1): 12416.

[5] Boettcher L N, Hssayeni M, Rosenfeld A, et al. Dual-task gait assessment and machine learning for early-detection of cognitive decline[C]//2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2020: 3204-3207.

[6] Zhang X, Xu F, Shi H, et al. Effects of dual-task training on gait and balance in stroke patients: A meta-analysis[J]. Clinical rehabilitation, 2022, 36(9): 1186-1198.

[7] Y. Hutabarat, D. Owaki and M. Hayashibe, "Recent Advances in Quantitative Gait Analysis Using Wearable Sensors: A Review," in IEEE Sensors Journal, vol. 21, no. 23, pp. 26470-26487, 1 Dec.1, 2021, doi: 10.1109/JSEN.2021.3119658.

[8] Soulard, J., Vaillant, J., Balaguier, R. et al. Spatio-temporal gait parameters obtained from foot-worn inertial sensors are reliable in healthy adults in single- and dual-task conditions. Sci Rep 11, 10229 (2021). https://doi.org/10.1038/s41598-021-88794-4

[9] L. Wang, Y. Sun, Q. Li, T. Liu and J. Yi, "IMU-Based Gait Normalcy Index Calculation for Clinical Evaluation of Impaired Gait," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 1, pp. 3-12, Jan. 2021, doi: 10.1109/JBHI.2020.2982978.

[10] T. Gujarathi and K. Bhole, "GAIT ANALYSIS USING IMU SENSOR," 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kanpur, India, 2019, pp. 1-5, doi: 10.1109/ICCCNT45670.2019.8944545.

[11] H. -C. Chang, Y. -L. Hsu, S. -C. Yang, J. -C. Lin and Z. -H. Wu, "A Wearable Inertial Measurement System With Complementary Filter for Gait Analysis of Patients With Stroke or Parkinson's Disease," in IEEE Access, vol. 4, pp. 8442-8453, 2016, doi: 10.1109/ACCESS.2016.2633304.

[12] Y. Hutabarat, D. Owaki and M. Hayashibe, "Quantitative Gait Assessment With Feature-Rich Diversity Using Two IMU Sensors," in IEEE Transactions on Medical Robotics and Bionics, vol. 2, no. 4, pp. 639-648, Nov. 2020, doi: 10.1109/TMRB.2020.3021132.

[13] Simon SR. Quantification of human motion: gait analysis—benefits and limitations to its application to clinical problems. J Biomech. 2004;37:1869–80.

[14] Hutabarat Y, Owaki D, Hayashibe M. Temporal Variation Quantification During Cognitive Dual-Task Gait Using Two IMU Sensors[C]//2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2022: 1121-1124.

[15] Oh C, LaPointe L L. Changes in cognitive load and effects on parameters of gait[J]. Cogent Psychology, 2017, 4(1): 1372872.

[16] Chiarello M, Lee J, Salinas M M C, et al. The Effect of Biomechanical Features on Classification of Dual-Task Gait[J]. IEEE Sensors Journal, 2022, 23(3): 3079-3089.

[17] Chang Yoon Baek, Woo Nam Chang, Beom Yeol Park, Kyoung Bo Lee, Kyoung Yee Kang, Myung Ryul Choi, Effects of Dual-Task Gait Treadmill Training on Gait Ability, Dual-Task Interference, and Fall Efficacy in People With Stroke: A Randomized Controlled Trial, Physical Therapy, Volume 101, Issue 6, June 2021, pzab067, https://doi.org/10.1093/ptj/pzab067

[18] Behboodi, A.; Zahradka, N.; Wright, H.; Alesi, J.; Lee, S.C.K. Real-Time Detection of Seven Phases of Gait in Children with Cerebral Palsy Using Two Gyroscopes. Sensors 2019, 19, 2517.

[19] Mo S, Chow D H K. Accuracy of three methods in gait event detection during overground running[J]. Gait & posture, 2018, 59: 93-98.

[20] Han S H, Kim C O, Kim K J, et al. Quantitative analysis of the bilateral coordination and gait asymmetry using inertial measurement unit-based gait analysis[J]. PLoS One, 2019, 14(10): e0222913.