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Seamless Temporal Gait Evaluation during Walking and Running Using Two IMU Sensors

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Abstract— **In this study, we proposed a framework for extracting gait events and extensive temporal features, seamlessly, during walking and running on a treadmill by constructing a finite state machine (FSM) transition rules based on two IMU sensors attached to the back of the shoes. Detailed inner-class states were defined to recognize the double support phase on walking gait and the double flight phase on running gait. Further, an in-depth speed-based analysis of temporal gait features can be performed for each tested speed with an automatic speed change detection algorithm based on the moving average filter applied to motion intensity data. The results have demonstrated that the FSM can accurately distinguish walking gait and running gait while also extract a detailed gait phase, respectively. This finding may contribute to a more flexible gait analysis where a change in speed or transition from walk to run can be anticipated and recognized accordingly.**

I. INTRODUCTION

Gait analysis can be used as a functional tool to assess a wide range of applications such as characterizing pathological gait, tracking rehabilitation progress, and also applied to various sports applications. Typically, gait analysis is performed under a laboratory setting comprised of motion capture and force plate systems for gold standard measurement, or motion capture and instrumented treadmill for a more detailed locomotion study with a controlled speed protocol. Both of those systems are costly, while the setup and operation can be time-consuming. The nature of this will limit the accessibility of using these gait analysis systems to only some research facilities.

On the other hand, recent advances in wearable sensors have made it possible to assess gait widely in a more natural or out-of-lab environment with relatively low cost as compared to the standard measurement. For example, a body-worn inertial measurement unit (IMU) has widely been used to analyze human motion in both indoor and outdoor settings [1],[2]. Several benchmark studies have been carried out to assess the agreement between wearable sensors and the gold standard measurement [3]-[5], where the potential and limitations were explained in detail.

A treadmill-based gait analysis enables a controlled speed experiment that is useful for tracking the gait performance of subjects across various speeds. Increased treadmill speed at some point will influence subjects to change their gait from walking gait to running gait. Some studies have argued that walk-run mixture at intermediate locomotion speed leads to optimization of metabolic energy [6].

Most of the state of the arts on wearable systems for gait analysis is developing a separate analysis between those two gait modalities [7]. We found that this study [8] discussed the assessment of temporal gait parameters using gyroscope during treadmill walking and running. But again, each of the tested speeds was captured and analyzed separately in different data recording sessions.

In this paper, we address this problem by introducing a framework that can incorporate both walking and running gait analysis, seamlessly by means of constructing a finite state machine (FSM) followed by detailed inner-class states in a single data recording session. Therefore in this paper, we proposed a controlled speed experiment on a treadmill to test our proposed framework. We have previously validated the performance of our algorithm to the gold standard measurement of motion capture and force plate systems on [5]. Although it has covered a wide range of self-selected speeds, it has not fully covered controlled slower and faster-walking speeds. Therefore we also aim to see the effect of those speeds on the gait of the subjects.

The rest of this paper is organized as follows. Section II discussed our proposed framework, experiments, and methods used in this study. Results and discussions are presented in Section III, which covers the overall temporal gait assessment results and interpretation. Finally, Section IV concludes the study and provides a direction for future research regarding this topic.

II. METHODS

A. Subjects

Four subjects participated in the study with a mean age of 24$\pm$1.4 years, mean height of 171.8$\pm$6.1 cm, and mean weight of 71.5$\pm$7.9 kg. All of the subjects reported that they have no severe lower limb-related injuries in the past year prior to the experiment. All subjects had given informed consent prior to participation in this experiment.

B. Data collections and preprocessing

In this study, all subjects wore two IMU (Trigno Research+, Delsys, MA, USA) wireless systems on the back of the shoes as presented in Fig. 1a. We selected this location as it was found to have 93 % in terms of accuracy for detecting the stride number [9]. In this study, 3-axis gyroscope and

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3-axis accelerometer data from each foot were considered. The sampling rate of the IMU sensors was set at 148 Hz. All the collected data were processed for analysis using MATLAB (Mathworks Inc., Natick, MA, USA). A 4th order Butterworth low pass filter was applied to all the collected data with a frequency cut-off of 6 Hz. After the filtering process, the data is ready to be used further for our designed algorithm to extract various temporal gait features.

C. Experiment protocols

Subjects were instructed to follow a pre-defined variable speed plan on a treadmill, starting from 2 km/h to 10 km/h, where the overall tested speed is $v = 2, 4, 5, 6, 8, 10$ km/h. During the experiment, subjects were also told to stop anytime if they felt uncomfortable. The purpose of this experiment was to see the effect of walking speed on temporal gait patterns for each subject. In addition to that, a comparison between subject-specific walking and running gait was also the interest of this experiment. The experiment was developed and performed according to the principles of the Declaration of Helsinki.

D. Temporal gait analysis

This section explains the overall procedure of the quantitative gait assessment (QGA) proposed in this study. As mentioned earlier, we used only two IMUs attached to the back of the shoes of each subject. Raw data from the IMU sensors were filtered using a 4th order Butterworth low pass filter with a cut-off frequency of 6 Hz. Following the filtering process, the data were processed according to the extracted gait features. The list of extracted features is presented in Table I.

1) Gait Event Detection: Gyroscope data were used to estimate three major gait events, i.e. initial contact (IC), toe-off (TO), and mid-swing (MSw). A heuristic threshold-based algorithm was constructed to detect these gait events. IC and TO were defined as the local maxima, whereas MSw was defined as the local minima detected from the gyro data. The same principles are applied to recognize running gait events, i.e. foot-contact (FC), foot-off (FO), and mid-flight (MF). Our detailed heuristics algorithm is available on [5].

2) Activity class: In this part of the study, we introduced three activity classes named walking, running, and others class, to easily distinguish certain movements performed by the subjects. Certain thresholds were defined to construct a finite state machine (FSM) transition rule between the activity classes, as depicted in Fig. 1a. The movement performed will fall under the 'walking' class if there are sequences of IC events detected. As two IMUs were used, the inner-class states could detect separately between left and right events, thus could lead to a more detailed double support analysis in walking class (Fig. 1b). On the other hand, if there is no initial and terminal double support detected, the movement will fall under the 'running' class (Fig. 1c). Any movement performed that did not satisfy any of the above-described states was classified as the 'others' class.

TABLE I
OVERALL EXTRACTED FEATURES

Features (f)	Unit	Description
Gait events	-	Consists of IC, TO, MSw, for walking gait; and FC, FO, and MF, for running gait
Stride time	s	Time needed to complete one gait cycle from IC to IC (walking/running)
Single Support time	s	Time elapsed when one foot is in contact with the ground (walking)
Double Support time	s	Time elapsed when both foot are in contact with the ground (walking)
Swing time	s	Time elapsed when foot is not in contact with ground (walking)
Contact time	s	Time elapsed when foot is in contact with ground (running)
Double Flight time	s	Time elapsed when both foot are not in contact with the ground (running)
Flight time	s	Time elapsed when one foot is not in contact with ground (running)
Gait phase	%	Percentage of average gait phase consisted of iDS, SS, tDS, SW for walking, and CP, iDF, FP, tDF for running
Symmetry Index	%	Symmetry feature based on stance time
Asymmetry Indices	s	Absolute mean difference of temporal features between sides (L&R)
Variability Indices	s	Various indices based on standard deviation of certain features
Activity class	-	0 for other activities, 1 for walking, 2 for running

3) Temporal features: Temporal features such as stride time, stance time, and swing time were derived based on the extracted gait events. Since we used two IMU sensors, in this study we calculated more detailed temporal features. Double support was estimated from the detection of IC of the left side to the detection of TO of the right side and vice versa. Initial and terminal double support, iDS and tDS, are interchangeable terms depending on the reference side. Similar to walking gait, on the running gait, initial and terminal double flight, iDF and tDF are interchangeable terms depending on the reference side.

Moreover, we also present these temporal features in terms of the percentage of each gait phase. Here we divided walking gait into four phases, consisted of iDS, SS, tDS, and SW, where SS and SW are single support and swing phases, respectively. Meanwhile, for running gait, we divided also it into four phases, consisted of iDF, CP, tDF, FP, where CP and FP are contact phase and single flight phase, respectively.

4) Other gait features: We derived four kinds of gait indices based on the extracted temporal gait features. Symmetry Index (SI) is a derived feature from the stance time of both sides. To calculate this feature, we averaged the total stance time of the left side to the right side for every walking or running class per experiment performed. The minus sign in SI indicates an overall less stance time on the left side while the positive sign indicates an overall less stance time on the right side. Asymmetry Indices (AIs) are various indices based on the absolute mean difference between left and right

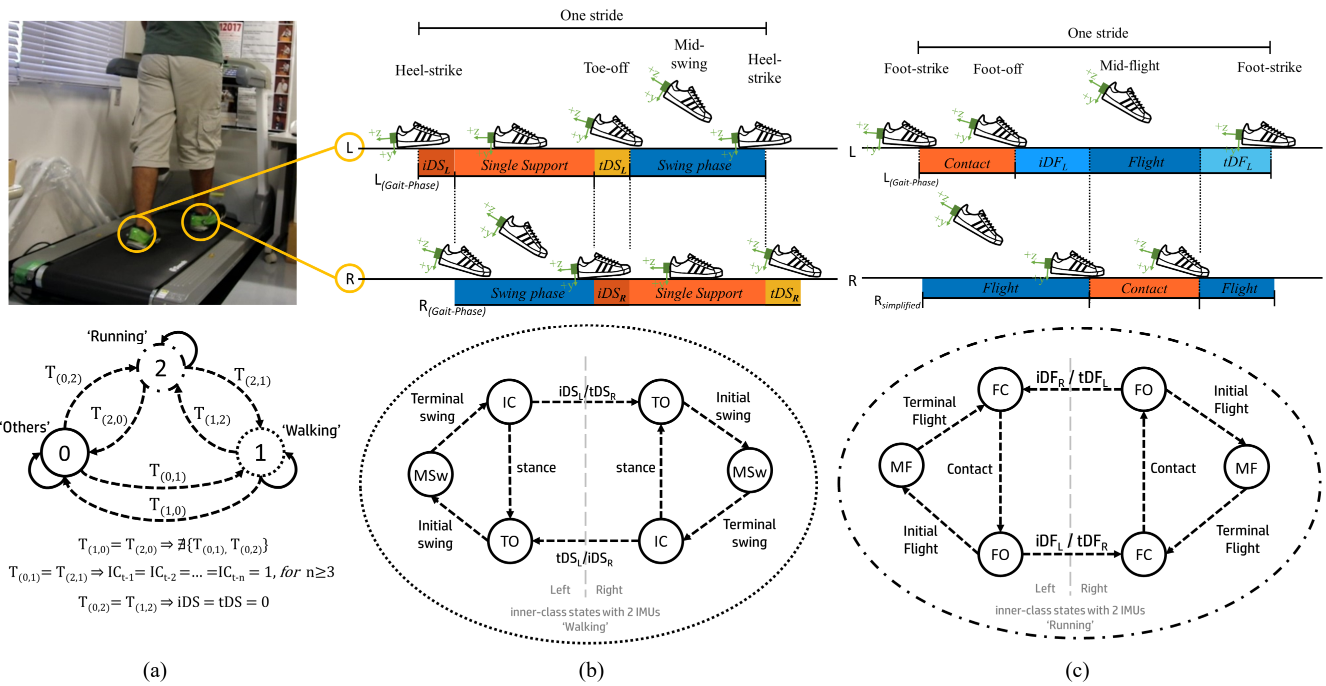

Fig. 1. The proposed framework of seamless temporal gait analysis during walking and running on a treadmill. (a) Example of a subject following the experimental protocols of controlled speed walking and running with two IMUs attached on the back of the shoes [top], with FSM class and transition rules that are applied in this study [bottom]. (b) Gait events and phases are recognized for walking gait [top] and the corresponded inner class states in FSM [bottom]. (c) Gait events and phases are recognized for running gait [top] and the corresponded inner class states in FSM [bottom].

TABLE II
PERCEPTION QUESTIONNAIRE

Subject	Comfort walking speed (km/h)	Transition speed (km/h)	Comfort running speed (km/h)
S01	5	6 to 8	10
S02	5	6 to 8	10
S03	4	6 to 8	10
S04	4	6 to 8	8

sides. AIs could potentially give important information about the subject-specific tendency of using left and right foot in gait. Variability Indices (VIs) are derived based on the standard deviation of temporal gait features. To give a more specific speed-based analysis, we can further detailed SI, AIs, and VIs based on speed to analyze how these indices changed over the increased speed of walking or running gait.

5) Speed change detection: In order to do a precise speed-based analysis, we introduce a speed change detection algorithm based on a simple moving average filter applied to Motion Intensity (MI) data [5], [10]. A 20-points moving average filter, MA_{20}, was found sufficient to capture the changing dynamic of MI data, which highly correlated with the changing in gait speed, based on several preliminary experiment trials. We set a threshold at 75^{th} percentile of the difference in MA_{20} value to determine if speed is constant or in transition. If MA_{20} crossed the threshold value, we marked it as a 'transition' state, while if it was under we marked it as a 'constant' speed state.

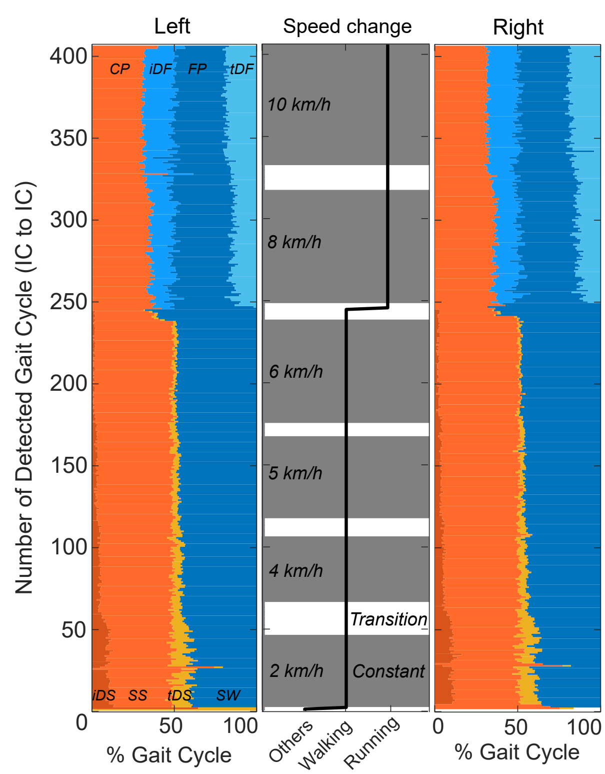

Fig. 2. Result from S01: Percentage of gait phases from a single experiment trial, where left and right gait can be quantified separately. Mid-figure depict the recognized activity class and the changing of speed throughout the experiment trial.

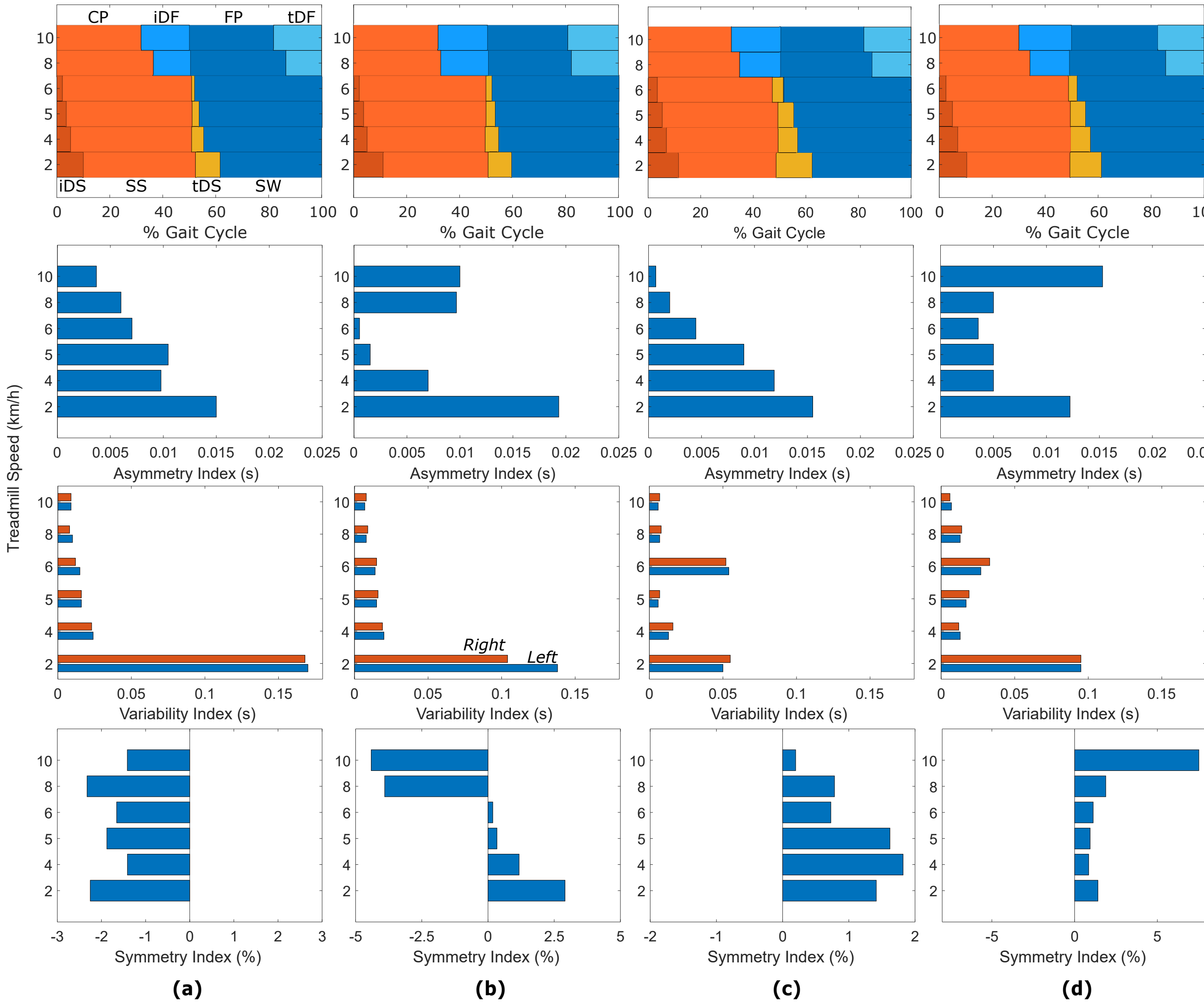

Fig. 3. Summary of temporal gait features distinguished by treadmill speed. Columns represent subjects, i.e. (a) S01, (b) S02, (c) S03, and (d) S04. Top row to bottom represent percentage of gait shares, asymmetry index, variability index, and symmetry index, respectively.

III. RESULTS AND DISCUSSIONS

We asked each of the participants about their perception of their gait during the experiment. Their responses have been summarized in Table II. This will help us to compare the perception of subjects and actual data-based results. In terms of the agreement to gold standard measurement, our framework in this study has been benchmarked to motion capture and force plate system as well as compared to various existing studies. The detailed discussion on this issue is out of the scope of this study but is extensively discussed on [5]. In the benchmark study, the temporal difference to force plate system were 4.22±15.48 ms (mean ± S.D.) and -8.31±21.02 ms (mean ± S.D.) for initial/foot contact and toe/foot-off events, respectively. Thus, in other words, we have verified that the accuracy of events detection falls roughly between 1-4 data samples (6.8 - 27.2 ms) at a 148 Hz sampling rate.

Data preprocessing, processing, and analysis were all done using a commercial PC with Intel Core i7-8750H 2.2 GHz CPU. All of the above processes were done in a specialized MATLAB-based application that we developed to execute the proposed framework. Demo software of this study is available on *https://github.com/yonatancah/Temporal-Gait-Evaluation*.

Figure 2 serves as an example of data analysis performed under the proposed framework for a single experiment trial. Here, the percentage of gait phases from the left and right sides of S01 is presented. A total of 406 gait cycles were detected from this experiment trial which lasted around 6 minutes and 20 seconds. The middle figure indicates the activity class as well as the point where constant speed or in 'transition' occurred.

Table III presents a detailed report on temporal features distinguished by the treadmill speed. Here we extracted iDS, SS, tDS, and SW time for walking gait and CP, iDF, FP, and tDF time for running gait. Walking gait was observed for 2,4,5, and 6 km/h treadmill speed, while running gait

TABLE III
QUANTITATIVE GAIT ASSESSMENT : A DETAILED REPORT ON TEMPORAL GAIT FEATURES DISTINGUISHED BY TREADMILL SPEED.

Subject	Mean Temporal Features (s)							Gait Indices			Treadmill Speed
	iDS	SS/CP	tDS	iDF	SW/FP	tDF	Stride time	SI (%)	AI (s)	VI (s)	
S01	0.105	0.452	0.113		0.432		1.102	-2.3	0.015	0.170(L) 0.168(R)	2 km/h
	0.047	0.432	0.052		0.443		0.973	-1.4	0.009	0.024(L) 0.023(R)	4 km/h
	0.027	0.438	0.034		0.449		0.948	-1.9	0.010	0.016(L) 0.016(R)	5 km/h
	0.011	0.422	0.019		0.430		0.882	-1.7	0.007	0.015(L) 0.012(R)	6 km/h
		0.250		0.097	0.258	0.100	0.704	-2.3	0.006	0.010(L) 0.080(R)	8 km/h
		0.215		0.126	0.220	0.127	0.688	-1.4	0.004	0.009(L) 0.009(R)	10 km/h
S02	0.134	0.636	0.178		0.615		1.564	2.9	0.019	0.138(L) 0.104(R)	2 km/h
	0.060	0.508	0.058		0.502		1.128	1.2	0.007	0.020(L) 0.019(R)	4 km/h
	0.038	0.478	0.039		0.479		1.034	0.3	0.001	0.015(L) 0.016(R)	5 km/h
	0.025	0.468	0.023		0.469		0.983	0.2	<0.001	0.014(L) 0.015(R)	6 km/h
		0.230		0.131	0.238	0.132	0.731	-3.9	0.009	0.008(L) 0.009(R)	8 km/h
		0.212		0.135	0.220	0.132	0.699	-4.4	0.01	0.007(L) 0.008(R)	10 km/h
S03	0.213	0.576	0.179		0.555		1.523	1.4	0.015	0.050(L) 0.055(R)	2 km/h
	0.085	0.479	0.780		0.466		1.108	1.8	0.011	0.013(L) 0.016(R)	4 km/h
	0.063	0.458	0.560		0.449		1.026	1.6	0.009	0.006(L) 0.007(R)	5 km/h
	0.041	0.413	0.320		0.444		0.930	0.7	0.004	0.054(L) 0.052(R)	6 km/h
		0.270		0.116	0.266	0.122	0.774	0.8	0.002	0.007(L) 0.008(R)	8 km/h
		0.236		0.136	0.234	0.142	0.747	0.2	<0.001	0.006(L) 0.007(R)	10 km/h
S04	0.186	0.601	0.159		0.577		1.522	1.4	0.012	0.095(L) 0.095(R)	2 km/h
	0.081	0.455	0.075		0.450		1.060	0.8	0.005	0.013(L) 0.012(R)	4 km/h
	0.056	0.423	0.048		0.419		0.946	0.9	0.005	0.017(L) 0.019(R)	5 km/h
	0.029	0.395	0.022		0.403		0.850	1.1	0.003	0.027(L) 0.033(R)	6 km/h
		0.245		0.104	0.251	0.106	0.706	1.9	0.005	0.013(L) 0.014(R)	8 km/h
		0.224		0.123	0.211	0.141	0.699	7.5	0.015	0.007(L) 0.006(R)	10 km/h

was observed for 8 and 10 km/h treadmill speed consistently across all subjects. These results are in agreement with self-reported assessment by the subjects as presented in Table II, where all subjects said that they changed from walk to run at 6 to 8 km/h transition. We observed that double support time, single support time, and contact phase time was decreased as treadmill speed increase across all subjects. On the other hand, even though we only have two speeds representing running gait, i.e. 8 km/h and 10 km/h, we observed that double flight time was increased as treadmill speed increase. These results are also presented in the top row of Figure 3 for every subject.

On gait indices, we presented SI, AI, and VI with respect to treadmill speed on Table III and Figure 3. On the results of SI, we found that it was unique to each subject. S01 showed an overall negative SI with an average of -1.83% SI in all tested treadmill speeds. S02 showed a decrement trend in SI starting from 2.9% SI on 2 km/h speed to -4.4 % SI on 10 km/h speed, with an average of 2.15 % SI. To be more precise, on walking gait we observed an overall positive SI, while on running gait we observed an overall negative SI. This means that on walking gait S03 and S04 showed an overall positive SI with an average of 1.08 % and 2.27 % of SI, respectively.

On the results of VI, we observed that the highest temporal variability on both left and right sides occurred on the slowest treadmill speed, i.e. 2 km/h. Interestingly, only S03 experienced another comparable high variability on 6 km/h treadmill speed, where left side variability was 0.054 s compared to 0.050 s on 2 km/h, and right side variability was 0.055 s on 2 km/h and 0.052 s on 6 km/h. One of the importance of looking at VI is that we can distinguish the timing variability of each side which can be useful to assess if there is impairment of one of the sides of the subjects. It should be noted that gait index scores may not give an absolute definitive condition of subjects, but it can be used as a relative measure to make an intra-subject comparison such as tracking rehabilitation progress or to make an inter-subject comparison between groups of interest [11].

On the computational time, we observed an average of 10.84 ± 0.59 s to finish computation and extract all of the features depicted in Table I, with an average experiment time across all trials of 417.95 ± 26.55 s. Note that this result was achieved using the computational hardware mentioned early in this section and executed in a MATLAB environment. Other processing hardware or programming language may result in different computational costs. Looking at the computational cost of around 11 seconds to complete roughly 7 minutes of data analysis, has made it highly possible for a real-time or online system to be constructed using our proposed framework.

IV. CONCLUSIONS

We have investigated our proposed framework of seamless extraction of temporal gait features for walking and running gait performed on a variable speed treadmill. By using two IMU sensors on both sides of the foot and introducing activity class with detailed inner-class states, we can successfully extract detailed gait phases both on walking and running gait that incorporate double support and double flight phases, respectively. In this study we also introduced a moving-average based filtering technique to filter out transition data between speed changing, thus a precise speed-based analysis can be performed. In sport application, this approach will contribute to investigating the consistency and performance of an athlete given a specific speed of treadmill training, in addition to a video-based analysis [12],[13]. To give a more in-depth analysis, we extracted several gait indices based on temporal features. These features are useful to be applied in a clinical setting such as to track rehabilitation progress and to compare data between subjects of interest [14],[15]. To conclude, the developed framework in this study would promote a more unrestrained gait analysis, where speed change and gait change can be anticipated and recognized, which reduces the amount of interruption to subjects during an experiment. Future work is to test it in an outdoor setting and considering a larger cohort and prolonged experiment time.

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