An Adaptive and Robust Online Method to Predict Gait Events

Stefan O. Schrade, Yvonne Bader, Michael R. Tucker, Camila Shirota, Roger Gassert
Rehabilitation Engineering Laboratory (RELab)
ETH Zurich, 8092 Switzerland
Website: <http://relab.ethz.ch>

Abstract—Accurate timing of interventions during the gait cycle are critical for optimal efficacy of assistive devices, e.g., to reduce the metabolic cost of walking. However, timing control generally relies on methods that can neither account for changes in the stride duration over time due to different walking speeds, nor reject isolated abnormal strides, which could be caused by stumbling or obstacle avoidance for example. In order to address these issues, a method, named the Gait Phase Estimator (GPE), is proposed to predict temporal gait events and stride duration. Predictions are based on the weighted forward moving-average of stride duration. Prediction performance in steady-state walking, robustness to stride disturbances, and adaptation to speed changes were evaluated in an experiment with three subjects walking on a treadmill at three different speeds. Results suggest that, on average, the GPE produces better predictions than a predefined estimate. On top, it automatically adapts to changes in speed, while offering the benefit of robustness to irregular strides unlike a conventional moving-average. Thus, the proposed GPE has the potential to improve and greatly simplify the process of obtaining stride duration estimates, which could benefit gait-assistive devices and experimental protocols.

I. INTRODUCTION

Timing of interventions during the gait cycle is critical for the efficacy of gait assistive devices, such as exoskeletons for human augmentation, e. g., to reduce the metabolic cost of walking [1], [2]. Exact timing is also needed for the exploration of human walking by applying well-timed perturbations to the leg [3]. For these applications, it is common that a constant estimate of stride duration – derived by averaging the stride duration over a period of steady-state walking [4], [5] – is used as a reference to control intervention timing. This is based on the rather constant stride duration of human walking at fixed speeds [6], and works well when strides are in fact consistent [7].

Constant estimates limit applications to fixed speeds, however. Furthermore, they are suboptimal when fatigue could affect stride time in long experimental protocols. This effect has been reported in running [8], [9] and could apply to walking as well. An altered stride time would deteriorate the precision of constant preset delays and thus, the timing of external interventions.

Some methods that adapt to a change in stride duration have been suggested. They rely on invariant trajectories

using a monotonically changing variable, e.g., the angle of the thigh relative to the ground, or the location of the center of pressure on the foot, to continuously estimate stride time [10]–[12]. However, they require more advanced instrumentation and must be calibrated to indicate occurring gait events. Additionally, this mapping could be afflicted with inter-subject variability and would then have to be repeated for each individual. Thus, a prediction algorithm directly relying on gait events is preferable, since stride duration is defined by gait events.

An online calculated forward moving-average of stride duration could adapt to changes in stride duration. However, abnormally long or short strides could drastically affect the estimates, since they are typically not rejected. Although they are generally rare, it is especially important to consider this, when they are induced as part of an experimental protocol, e. g., in experiments involving perturbations to the subject's gait [3]. In the course of such experiments, irregularities are expected to be present during perturbations, and while the subject recovers. Disturbances that are part of the protocol are predictable, since they are planned, and could therefore be ignored manually. Other irregularities induced by foot scuffing during swing, or avoiding an obstacle cannot be foreseen and need to be dealt with automatically when they occur. Hence, a practical algorithm should be robust against irregular strides.

An adaptive method that estimates the stride duration by predicting the next stride's gait events is presented. A weighted average of previous strides in a moving window is used to calculate the estimates. The weighting assigns low weights to individual strides differing from the others in the moving window. This results in robustness to isolated stride abnormalities. Said method, named the Gait Phase Estimator (GPE), is compared to a preset constant estimate and a non-weighted forward moving-average. The preset constant estimate represents the most commonly used method to predict gait, whereas the forward moving-average is an easy way of implementing an adaptive stride estimation. The prediction accuracy of the algorithms during steady-state walking, speed transitions (adaptability), and with deliberately long strides (robustness to abnormal strides) during treadmill walking is evaluated at three different speeds. The results suggest that the GPE is a promising method to automatically provide accurate estimates of stride duration even when the speed

is changed or irregularities are present in gait.

II. METHODS

A. Application Scenario

Focusing on real-time applications, the algorithm was required to be implementable in a system running at 1 kHz on a Simulink Real-Time (The Mathworks, Natick, MA) target machine. Further, gait events - such as initial contact and end contact - were assumed to be provided by the system's instrumentation. These events are ubiquitously used in gait assistive devices, and can be derived from foot switches, force plates, IMUs, etc. In this paper, pneumatic foot switches under the toe and heel region of each foot were used to detect gait events, i.e., heel-strike, toe-strike, heel-off and toe-off.

B. Gait Phase Estimator Algorithm

State-of-the-art stride estimation cannot accommodate for changes in stride duration, or reject spurious, abnormal strides. To address these issues, a weighted forward moving-average, which attenuates outlier strides, is proposed. This method is based on the assumption that stride duration is consistent over a (short) period of time, and is best predicted by a cluster defined by the previous strides. Assuming a single cluster, each previous stride's weight for the calculation of the mean can be inferred from a Gaussian probability density function.

First, the standard deviation and mean were calculated for the stride durations, x_i , that occurred in the window (1). A probability density function for a population with Gaussian distribution was evaluated (2), resulting in the probability d_i of each stride duration. The results were normalized (3) with the sum over all d_i (4) and used as weights w_i for the computation of a weighted mean (5). This weighted mean served as the following stride's duration estimation.

$$\mu = \frac{\sum_{i=1}^n (x_i)}{n}, \sigma = \sqrt{\frac{\sum_{i=1}^n [(x_i - \mu)^2]}{n - 1}} \quad (1)$$

$$d_i = f(x_i | \mu, \sigma) = \frac{1}{(\sigma \sqrt{2\pi})} e^{-\frac{(x_i - \mu)^2}{(2\sigma^2)}} \quad (2)$$

$$w_i = \frac{n \cdot d_i}{w_{tot}} \quad (3)$$

$$w_{tot} = \sum_{i=1}^n d_i \quad (4)$$

$$\bar{\mu} = \frac{\sum_{i=1}^n (x_i \cdot w_i)}{n} \quad (5)$$

C. Experimental Protocol

In order to evaluate the prediction performance of the proposed GPE, an experiment was conducted with three unimpaired subjects (Tab. I). The experiment was approved by the Cantonal Ethics Commission of Zurich (KEK-ZH 2014-0049).

The experiment comprised of steady-state walking, robustness and speed adaptation conditions (Fig. 1) recorded at

TABLE I
RELEVANT SUBJECT DATA

subject	gender	age [years]	weight [kg]	height [m]
1	F	25	67	1.66
2	M	27	94	1.98
3	M	28	75	1.78

Fig. 1. Diagram of the experimental protocol illustrating the conditions employed to examine steady-state walking prediction, robustness against irregular strides and speed adaptation.

1.2 m/s, 1 m/s and 1.4 m/s in that order for all subjects. Each speed sequence of the experimental protocol started with a 2 min period of treadmill walking for acclimation, which was not used for the data analysis. The following 25 strides were averaged to generate a fixed prediction of the stride time [4]. Then, a 2.5 min sequence of steady-state walking was recorded. Subsequently, the subject was instructed to make deliberate changes in stride duration by taking longer steps with the right foot. Two sets of temporal outlier patterns were recorded. In the first series, 4 long steps with a temporal spacing of 15 s were performed. The second set comprised 6 long steps with 10 s spacing. The subject was instructed to follow an auditory signal generated by the computer in order to adhere to the desired long step timing. Recovery from the long steps was assured by recording a 1 min walking period succeeding each series of long steps. By defining two different narrow-spaced perturbation patterns including recovery time, robustness could be assessed, while it was still reasonable to assume that the stride duration would not change meaningfully. Finally, the subject was instructed to change the treadmill belt speed and the sequence was repeated for the new speed.

D. Data Analysis

The performance of the GPE was evaluated in the three conditions: steady-state walking, walking with irregular strides, and during walking speed transitions. The GPE was compared to the constant estimate (standard method) and non-weighted moving-average (standard adaptive method). When comparing the methods, the GPE and the non-weighted moving-average window length were chosen to be 25, in order to match the number of strides used for the preset estimate. The prediction error was the difference between estimated stride duration and 'true' value obtained from foot-switches, calculated as time from one initial contact to the

next initial contact of the right foot. Errors were normalized by the true duration of each stride. An overall performance indicator was calculated in each testing condition, obtained as the average prediction error of that method across all speeds and subjects.

As the GPE relies on a number of strides to generate predictions, the influence of the window length on the prediction accuracy was examined by post-processing the data with simulated lengths between 2 and 30. The window length resulting in the smallest average prediction error over all subjects, speeds and conditions was defined to be optimal.

III. RESULTS AND DISCUSSION

A. Steady-State Walking

During steady-state walking, the GPE had slightly better predictions on average than a preset constant. As expected, the moving-average yielded very similar estimates to the GPE, since no outliers were recorded (Fig. 2). While the constant estimate of stride time already resulted in a low average error of 1.27 % stride, the GPE decreased the error to 1.02 % stride. The results for each subject and speed can be found in Table II.

In this experiment, no long-term drift of stride duration was found. This could, however, be different for longer protocols, as fatigue has been shown to cause cadence changes in running [8], [9].

The average tended to oscillate around or near a constant value, which was rather well captured by the preset estimate, explaining the good performance of the constant estimate.

Fig. 2. Representative stride duration estimates during steady-state walking. Constant (black dash-dotted), non-weighted moving-average (green dotted) and GPE (red solid) estimates are presented over the detected (gray solid) stride duration. Note that the non-weighted average and the GPE only differ slightly without any irregularities present. Data are from subject 1 at 1.4 m/s.

B. Robustness Against Outliers (Long Strides)

When irregular strides were deliberately introduced in the data sets by the subjects, the GPE also generated a more accurate average prediction than the preset estimate and the

TABLE II
AVERAGE PREDICTION ERROR OF THE GPE AND CONSTANT ESTIMATE METHODS, IN % STRIDE

subject		1		2		3	
steady-state walking							
		GPE	const	GPE	const	GPE	const
speed	1 m/s	1.17	1.38	1.17	1.17	1.08	1.44
	1.2 m/s	0.95	1.18	1.55	1.70	0.73	0.76
	1.4 m/s	0.70	1.02	1.13	1.50	0.75	1.27
long steps							
		GPE	const	GPE	const	GPE	const
speed	1 m/s	2.26	2.48	4.13	4.07	3.33	6.14
	1.2 m/s	1.75	2.26	2.24	3.02	3.13	4.06
	1.4 m/s	1.40	1.83	1.78	2.03	3.38	3.57

non-weighted moving-average (Table II). The GPE's online adaptability to the more irregular gait allowed more accurate predictions than a preset estimate.

The difference in average accuracy between GPE and constant estimate was larger in the sequences testing robustness in comparison to the steady-state walking condition. This could be explained by the subjects altering their stepping in preparation for longer steps, which interrupted their regular cadence and deteriorated the constant estimate's prediction. Additionally, a typical, more irregular recovery phase could be observed after each long step (Fig. 3). Both made the walking generally less steady during this condition, which the GPE could predict more precisely than a constant estimate by adapting its prediction online. Subject 3 seemed to benefit the most from the adaptive behavior of the GPE as seen at speeds of 1 and 1.2 m/s.

The individual long steps had a large error for all prediction methods. This was expected, since they cannot be accounted for by any of the tested methods. It is noteworthy that in one long step sequence of subject 2, the GPE performed slightly worse than a fixed estimate, which did not agree with the other collected data. This period was the only that contained one stride detected to be 0.4 s. This stride caused a very high error of around 250 % for all methods, which explains the unusually high average seen in Table II (subject 2, 1 m/s). The unplanned disturbance influenced the GPE for multiple steps, leading to a slightly worse average error in this specific sequence.

The non-weighted moving-average could adapt to the more irregular gait. However, its prediction accuracy was deteriorated after each long step. This indicates the efficacy of the attenuation of the irregular strides' effects in the GPE.

C. Speed Transitions

When the cadence was rapidly changed by altering the treadmill belt speed, the GPE estimate followed the new cadence with a delay depending on the window length n , as expected (Fig. 4). When different walking speeds are part of the protocol, the constant estimate either has to

Fig. 3. Long steps cause clearly visible altered stride times (gray line) that cause a drift of the non-weighted estimate visible after the peaks (green dotted line) whereas the GPE estimate follows the actual strides more accurately (red solid line). The preset estimate (black dash dotted) is not influenced by the long steps. However, it can also not adapt to an altered stride duration in preparation for and after longer steps. Data are from subject 1 at 1.2 m/s.

be calculated from a sequence of walking at all speeds in advance, or after an acclimation period every time the speed is modified. Both options lengthen the experimental protocols and complicate data collection. This illustrates the advantage of the automated adaptation to new stride durations with the GPE, since it facilitates the experimenter's work. The GPE leverages its potential even more if speed changes that are not induced by the experimenter occur slowly due to, e.g., fatigue in a long protocol or other unforeseen factors. In this case, an adaptation is not possible for a preset estimate and could only be achieved by manually adapting it from time to time.

D. Window Length

The maximum GPE window length n considered for the comparison was set to 30 strides, which assured satisfactory online calculation capability. In order to identify the optimal length, the influence of n was examined offline with the recorded data set by varying it from 2 to 30 samples. The average error over all speeds and subjects for each condition is shown in Fig. 5. By minimizing the sum over all three curves, the optimal window length was found to be 7.

The optimal window length is likely to be influenced by the experimental protocol, because the temporal spacing of regularly occurring perturbations could influence the minimum size, i.e., the amount of regular strides needed to counteract an irregular one. Some observations, however, are expected to be independent of the experiment. Increased window length will lead to an adaptation delay and an increased error whenever cadence changes, while a very short window will be more prone to estimation errors due to irregularities. As a consequence, the average error of the individual conditions could be weighted for optimization in regard to an application

Fig. 4. The adaptation time of the GPE estimate (bold red solid for $n=25$) is influenced by the window length. The family of curves for a size variation from 2 to 30 is indicated by the gray area and demonstrates the impact of n on the adaptation delay, which is proportional to the number of steps in the window. The preset constant for the new velocity can only be calculated in advance with a number of recorded strides or after some time at the new speed. Data show subject 2 in speed adaptation from 1 m/s to 1.4 m/s.

such that, e.g., a very fast adaptation would be emphasized and preferred over robustness. Depending on the emphasis, the optimal window length would then be shifted to longer or shorter lengths.

Fig. 5. The GPE estimation error averaged over all subjects and all speeds are shown for all three conditions (red). As a comparison a non-weighted moving-average prediction is shown (green). The difference between the two methods is very apparent in the long step condition for almost all window lengths, while there is only a marginal difference in the other conditions. When speed changes occurred, the average error was proportional to the window length. The attenuation noticeably improved the result in the long step condition. However, a plateau was reached before $n=10$. Estimations with more strides showed no beneficial effect in this condition.

E. Future Work

Future work could include refinements of the GPE algorithm. A correction for over- and underestimation, based on the assumption that the following step will be deviating in

the opposite direction by a comparable amount to keep up a constant walking speed, could be of special interest for examination. Alternative ways of suppressing unusual stride data are possible building on the idea of attenuating outliers. These may decrease the number of necessary strides in the window and make the estimator more agile and flexible.

If the GPE were to be applied in overground walking for online control of, e.g., a prosthetic device, it would not be an adequate solution for tasks where the cadence fluctuates rapidly, as when transitioning from standing to walking, or navigating through a crowd at a cocktail party. It could, however, be used for predictions in constant speed phases of overground walking. Experiments without the treadmill could deliver valuable insights into this.

A stride prediction method to correctly time interventions could also be useful for gait therapy such as functional electrical stimulation with spinal cord injury patients [13]. Even though only healthy subjects were examined in this pilot study, the method is expected to work if the impaired gait is periodic even when asymmetric. The walking speeds that should be tested for subjects exhibiting impaired gait are expected to be lower. This could increase the variability of gait. The accuracy of the GPE and every other prediction method is limited by the inherent variability of the subject's gait if their estimates are based on previous strides. Additional to the reduced walking speed, more unpredictable irregularities could be expected in pathological gait due to, reduced strength of the dorsiflexor muscles resulting in scuffing of the foot during swing for example. This would be a strong argument to use the GPE as it is able to reject these irregularities.

It is noteworthy that only initial contacts were analyzed to evaluate the performance of the GPE for stride time estimation in this article. However, the same algorithm can be applied to other gait events, i. e. end contact. In combination, stride duration and toe off estimation yield swing and stance phase duration. This was employed in the gait exploration study [3] to target swing phase specifically.

IV. CONCLUSION

The GPE predicts stride time in steady-state treadmill walking with higher average accuracy than a fixed stride time estimate. The main benefit of the GPE is that it adapts to variations in stride duration without manual intervention. The GPE was also able to accurately predict strides despite deliberately long steps and the irregular cadence induced by them. Thus, it is suitable for applications in need of predictions for temporarily disturbed walking. The GPE can be adapted to the particular application by varying the window length. Short windows favor the estimate's adaptation speed, while a longer window can be more robust.

Thus, the GPE can be used for assistive gait interventions or research protocols that involve multiple walking speeds with healthy subjects even when irregularities occur. The biggest advantage is that it enables the experimenter to focus

on other tasks rather than sampling sequences of gait needed to calculate a preset estimate.

ACKNOWLEDGMENT

The authors would like to thank William R. Taylor and his colleagues for the interesting discussion on this topic, and for their inputs.

REFERENCES

- [1] P. Malcolm, W. Derave, S. Galle, and D. De Clercq, "A simple exoskeleton that assists plantarflexion can reduce the metabolic cost of human walking," *PloS one*, vol. 8, no. 2, p. e56137, 2013.
- [2] P. Malcolm, R. E. Quesada, J. M. Caputo, and S. H. Collins, "The influence of push-off timing in a robotic ankle-foot prosthesis on the energetics and mechanics of walking," *Journal of neuroengineering and rehabilitation*, vol. 12, no. 1, p. 1, 2015.
- [3] M. R. Tucker, A. Moser, O. Lamercy, J. Sulzer, and R. Gassert, "Design of a wearable perturbator for human knee impedance estimation during gait," in *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*. IEEE, 2013, pp. 1–6.
- [4] T. M. Owings and M. D. Grabiner, "Measuring step kinematic variability on an instrumented treadmill: how many steps are enough?" *Journal of biomechanics*, vol. 36, no. 8, pp. 1215–1218, 2003.
- [5] A. J. Stevenson, S. S. Geertsen, J. B. Andersen, T. Sinkjaer, J. B. Nielsen, and N. Mrachacz-Kersting, "Interlimb communication to the knee flexors during walking in humans," *The Journal of physiology*, vol. 591, no. 19, pp. 4921–4935, 2013.
- [6] J. M. Hausdorff, H. K. Edelberg, S. L. Mitchell, A. L. Goldberger, and J. Y. Wei, "Increased gait unsteadiness in community-dwelling elderly fallers," *Archives of physical medicine and rehabilitation*, vol. 78, no. 3, pp. 278–283, 1997.
- [7] M. R. Tucker, J. Olivier, A. Pagel, H. Bleuler, M. Bouri, O. Lamercy, J. del R Millán, R. Riener, H. Vallery, and R. Gassert, "Control strategies for active lower extremity prosthetics and orthotics: a review," *Journal of neuroengineering and rehabilitation*, vol. 12, no. 1, p. 1, 2015.
- [8] I. Hunter and G. A. Smith, "Preferred and optimal stride frequency, stiffness and economy: changes with fatigue during a 1-h high-intensity run," *European journal of applied physiology*, vol. 100, no. 6, pp. 653–661, 2007.
- [9] J. A. García-Pérez, P. Pérez-Soriano, S. Llana, A. Martínez-Nova, and D. Sánchez-Zuriaga, "Effect of overground vs treadmill running on plantar pressure: Influence of fatigue," *Gait & posture*, vol. 38, no. 4, pp. 929–933, 2013.
- [10] N. Borghese, L. Bianchi, and F. Lacquaniti, "Kinematic determinants of human locomotion," *The Journal of physiology*, vol. 494, no. Pt 3, p. 863, 1996.
- [11] R. D. Gregg, E. J. Rouse, L. J. Hargrove, and J. W. Sensinger, "Evidence for a time-invariant phase variable in human ankle control," *PloS one*, vol. 9, no. 2, p. e89163, 2014.
- [12] M. A. Holgate, A. W. Böhrer, and T. G. Sugar, "Control algorithms for ankle robots: A reflection on the state-of-the-art and presentation of two novel algorithms," in *Biomedical Robotics and Biomechanics, 2008. BioRob 2008. 2nd IEEE RAS & EMBS International Conference on*. IEEE, 2008, pp. 97–102.
- [13] D. Popović, R. B. Stein, N. M. Oğuztöreli, M. Lebedowska, and S. Jonić, "Optimal control of walking with functional electrical stimulation: a computer simulation study," *Rehabilitation Engineering, IEEE Transactions on*, vol. 7, no. 1, pp. 69–79, 1999.