Online Learning of Gait Models for Calculation of Gait Parameters

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***Abstract*— This paper proposes a novel approach for gait analysis from wearable sensing, based on an adaptive periodic model of any gait signal. The proposed method learns a model of the gait cycle during online measurement, using a continuous representation that can adapt to inter and intra-personal variability by creating an individualized model. Once the algorithm has converged to the input signal, key gait events can be identified relative to the estimated gait phase; these events can then be used to calculate gait parameters. The approach is implemented and tested on a human motion dataset where heel impact and toe takeoff events are extracted with an average error of 0.04 cycles.**

I. Introduction

Accurate and individualized measurement and modeling of gait is useful in many applications, such as fall risk assessment [1]. Gait classification and analysis is frequently based on gait parameters such as step-to-step variability, single support time, double support time, cadence, and step length [2], [3], [4]. Most of the gait parameters listed above are calculated from the identification of gait events, particularly heel impact (HI) and toe take-off (TT).

Most gait analysis in clinical settings is based on visual observation which lacks sensitivity; whereas more advanced gait analysis techniques are typically too expensive and time-consuming. Sometimes quantitative measures such as Timed Up and Go [5], [6], [7] and timed gait trials [8], [9] are used, but these only indirectly measure the quality of motion.

Recently, the use of microelectromechanical systems (MEMS) inertial measurement unit (IMU) sensors has led to research on quantitative measurement of gait parameters. IMUs, typically attached at the ankle, provide a continuous measure of the linear acceleration and angular velocity during gait. In [10], thresholds on the acceleration signal are used to extract peaks in sagittal and vertical directions. A Bayesian classifier is then used to determine whether a peak corresponds to a stride. An accuracy of 98% was reported for stride detection; however, the thresholds and Bayesian classifiers depend on whether the user is young or elder.

In [11], frontal angular velocity signals are thresholded to detect heel impact and toe takeoff events. A stride length error of approximately 3% was reported; however, this method was only tested on five healthy individuals.

The majority of algorithms used to estimate gait parameters are threshold-based [10], [11], [12], [13], [14], [15], making them sensitive to threshold parameters and causing poor generalization to new data (*e.g.*, different gait type, ground surface, sensor placement, footwear, etc.). Some machine learning techniques have been implemented [16], [17], however, these methods use offline training and do not generalize well to data that is different from the training set. Therefore, it is desirable to use an algorithm which generates a richer, more representative model that generalizes to a large variety of input data. From this model, objective measurements such as gait parameters can be derived.

Recently, Joukov et al. [18] proposed an approach for gait pose estimation from wearable inertial sensors, using a rhythmic extended Kalman filter (EKF). Gait patterns are modeled using a Fourier time-series representation which estimates measured angular velocity terms. For this approach, the canonical dynamical system (CDS) [19] model of gait is learned during online observation, which can then be used to segment the motion data into strides based on the phase, with a segmentation accuracy of 97%.

In this paper, we propose using the CDS to model gait as a periodic signal whereby phase values are able to align gait events that occur from stride to stride, from trial to trial, and from individual to individual. This method of gait modelling does not require the use of thresholds and can be applied to any data that is periodic.

II. Methods

This paper proposes a method to model the phase of the gait cycle from any measured signal. More precisely, gait data will be modeled as a periodic signal with a continuous phase variable, allowing data corresponding to each foot to be automatically labeled as in-step or in-swing (hence providing the time of toe take-off and heel impact). This model can be used to directly calculate gait parameters as well as their variability over multiple gait cycles.

A. Gait Model

Model parameters (*i.e.* frequency and magnitude of gait) differ for each individual and may also differ between legs for individuals with asymmetric gait. Furthermore, within a single individual, gait parameters may change over time due to disease progression or due to improvement from treatment. To obtain an accurate, individualized model of gait, we learn the model parameters online during observation, using incremental updates to the parameters based on the error between the model-predicted and measured signal. The reduction of this error corresponds to learning model parameters that more closely fit the measured signal; the model representation allows us to extract an estimate of the phase.

We model gait using the CDS Fourier series representation

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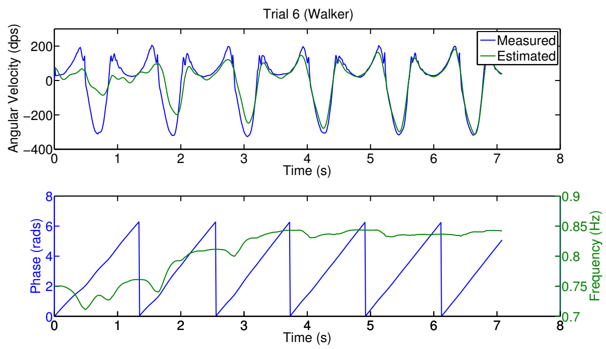

Fig. 1: Learning of a Gait Model. The top panel shows the measured left ankle frontal angular velocity in blue and the corresponding estimate in green; after five cycles, the two signals appear almost identical. The bottom panel shows the estimated phase in blue (left vertical axis) and the estimated frequency in green (right vertical axis).

introduced by Petriĉ et al. [19], described by:

$$\hat{y} = \sum_{m=0}^{M} \left(\alpha_m \cos\left(m\phi\right) + \beta_m \sin\left(m\phi\right)\right) \tag{1}$$

where $\hat{y}$ is the estimated signal, M is the number of harmonics in the estimated signal, α_m and β_m are the m^{th} frequency coefficients of the estimated signal, and ϕ is the estimated phase. To learn the model, the system parameters are updated as follows:

$$\begin{aligned} e &= y - \hat{y} \\ \phi &\longleftarrow mod(\phi + T(\omega - \mu e \sin\left(\phi\right)), 2\pi) \\ \omega &\longleftarrow \left|\omega - T\mu e \sin\left(\phi\right)\right| \\ \alpha_m &\longleftarrow \alpha_m + T\eta e \cos\left(m\phi\right) \\ \beta_m &\longleftarrow \beta_m + T\eta e \sin\left(m\phi\right) \end{aligned} \tag{2}$$

where y is the actual signal, e is the error between the estimated and actual signals, ω is the estimated angular frequency, μ is the frequency learning rate, η is the coefficient learning rate, and T is the sampling period. Note the angular frequency is equal to the cadence of the individual since gait events repeat each gait cycle (where angular frequency is the frequency multiplied by 2π).

The variables above can be divided into a set of adaptable parameters which are updated as the incoming signal is learned (ϕ, ω, α, β) and a set of constant parameters which are predetermined (M, μ, η).

To initialize a model, we start with initial values for the adaptable and constant parameters. The adaptable parameters will then be updated based on the incoming data to create a model that more closely describes the data. The error between the estimated and the measured signals will be used at each time step to update the adaptable parameters. Figure 1 illustrates the learning process.

B. Event Identification

Once the estimate has converged to the actual signal (the gait model has been learned), we wish to identify the gait events, in particular heel impact and toe takeoff. Once these events are identified relative to the estimated gait phase, the CDS algorithm can automatically identify any future events since we assume they occur at the same phase, as is common in gait analysis [20]. We compare two approaches; each identifies the phase corresponding to heel impact and toe takeoff events in the first cycle that meets the convergence criteria (see Section III-B) and then identifies all events in subsequent strides by assuming they occur at the same phase.

1) Heuristic: To identify an event relative to the gait phase determined by the model, we developed heuristics based on ankle frontal angular velocity signals motivated by [11], to identify the gait events as follows:

- Heel impact: The phase of the first local minimum following the maximum value (cycle values are re-ordered to start at the index of the maximum value and wrap around to the index prior);
- Toe takeoff: 1.25π after the heel impact event.

Since the heel impact event is the easiest to identify heuristically and because we observed that toe takeoff often occurs approximately 1.25π after heel impact, we identify the TT event *relative* to the HI event.

This method of event identification is shown in Figure 2. The identified heel impact and toe takeoff events are similar to those obtained from the footswitch signals.

However, because IMU data is very sensitive to orientation changes that cannot be perfectly controlled and heuristic methods are sensitive to the signal form, this method does not work correctly for all data.

2) Manual: The phase corresponding to the ground truth (GT) event time was extracted from the footswitch data in the first "converged" stride. Events are automatically identified in subsequent strides at the same phase values. The above manual event phase labeling was done only for the first "converged" stride of each trial.

C. Data Collection

Data from 16 healthy participants was collected at the Neuroscience, Mobility and Balance lab at the University of Waterloo (67% male, age = 25±4 years, height = 171±5 cm, weight = 66 ± 10 kg). Subjects were asked to to do a variety of gait types, including walking at their preferred pace, walking using a walker, walking using a cane, walking slowly, walking with a simulated single limb impairment (asymmetric), walking in a large circle, and walking at

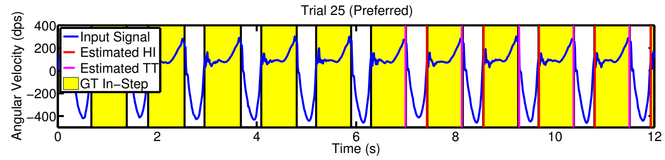

Fig. 2: CDS Heuristic and Ground Truth Event Identification. The blue line shows the left ankle frontal angular velocity signal. The vertical red and pink lines show the HI and TT events, respectively, as identified by the heuristic event identification. The starts and ends of sections highlighted in yellow show the locations of HI and TT events identified from GT data, respectively. As desired, vertical red lines coincide with the starts of highlighted sections and pink lines coincide with the ends of highlighted sections.

varying speeds (slow-fast-slow). Slow, preferred, and fast speeds were self-selected. The trials were either 12.2 or 19.9 meters in length, with the exception of the turn trials, which were each approximately 41.7 meters.

Both linear acceleration and angular velocity (along sagittal, frontal, and vertical axes) were collected from Shimmer[1] IMUs attached to individuals' right ankle, left ankle, right hip, and sternum. Accelerometer and gyroscope data was collected at 102.4 Hertz with sensitivities of $\pm$(2-8) G-force and ± 500 degrees per second (dps) respectively. For ground truth measurements, Bortec[2] footswitch cells were placed at the toe and heel of each subject's foot, either under the insoles or directly under the shoes.

A total of 285 trials were used. The study was approved by the University of Waterloo Research Ethics Board and consent was obtained from all participants, following a pilot data collection.

III. Results

While the proposed method can be applied to any continuously measured signal, here we use the left-ankle frontal (Y-axis) gyroscope signal. We chose this as input since gyroscope data is less noisy than accelerometer data and the angular velocity along the frontal axis intuitively carries the most information for lower limb motion. We have discarded all other information because only one signal is necessary to determine the phase of the gait cycle; once this phase is learned, it can be applied to all measured signals.

A. Parameter Initialization

The parameter initialization values were chosen empirically and are as follows: $\omega = 2\pi(\frac{3}{4})$ rads/s $= \frac{3}{4}$ Hz; $\phi = 0$; $\alpha_m = 10, \forall m$; $\beta_m = 5, \forall m$; $M = 6$; $\mu = 0.01$; and $\eta = 1$.

For the adaptable parameters, these are only initial settings adapted during online observation; however, the closer the initial guesses are to their true values, the more quickly the algorithm is able to learn the corresponding model. While moderate intensity walking is approximately 100 steps/min (50 gait cycles/min) [20], we plan to apply this algorithm to a large variety of gaits, including much slower gaits. We also want the fundamental frequency to coincide with the subject's cadence and therefore need to be careful that our initial frequency is not closer to a multiple of the fundamental frequency than to the fundamental frequency. Hence, we have chosen our frequency, ω, to be 45 cycles/min $= \frac{3}{4}$ Hz. Figure 1 shows the learning of a gait model using parameter initializations as described above.

B. Convergence Criteria

Before events can be identified by the CDS algorithm, the predicted signal should have converged to the actual signal. We assume convergence has been reached (the model has been learned) once the sum of the average absolute error over the previous 150 samples is below 30 degrees/second.

[1]Shimmer Research, www.shimmer-research.com

[2]Bortec Biomedical Ltd., www.bortec.ca

TABLE I: Performance Measures

	Seconds	Cycles
Convergence Time	6.74 ($\pm$3.25)	5.46 ($\pm$2.38)
Event Time Error		
Heuristic	0.11 ($\pm$0.15)	0.08 ($\pm$0.11)
Manual	0.05 ($\pm$0.12)	0.04 ($\pm$0.08)

C. Validation

The proposed method is compared to GT data by a validation routine that measures both the accuracy of the algorithm and the amount of time it takes to meet the convergence criteria. The accuracy measurement focuses on the recognition of heel impact and toe takeoff events of the gait cycle.

1) Performance Analysis: Three values of particular interest are the percentage of trials that meet the convergence criteria, the time these trials take to meet the criteria, and the error in estimated event times for these trials.

The impact event time error is computed by taking the absolute difference between each impact event identified by the CDS method and the corresponding impact event from the ground truth data. This means that if there is an error in the frequency estimation, the error could be larger than one cycle. For this reason, if the error is greater than one cycle, we set that error to the cycle length (taken to be the average length between impact events, as determined by the ground truth data). The takeoff event time errors are similarly computed; the overall event time error is taken as the average of the impact and takeoff event time error. To ensure that events identified by the CDS and the footswitches can be compared, if the CDS and ground truth event estimates finish with different event types, we remove the last event.

The results for the convergence criteria defined in Section III-B are shown in Table I; 93% ($\frac{264}{285}$) of the trials met these criteria. The mean ($\pm$ standard deviation) is shown for each performance measure. The criteria for convergence are met in about 5 strides. Manual event identification performs better than heuristic event identification, as expected. The heuristic approach results illustrate the achievable performance if GT footswitch data is not available.

Table II shows the percentage of trials that met convergence criteria for each gait type, and of those, the associated convergence time and event time error when using manual event identification. Performance is excellent across a variety of gait types, including asymmetry and assisted gait. The varying speed trials contain most of the trials for which the algorithm did not meet convergence criteria; this is likely because the gait frequency continues to change and the algorithm does not always reach the convergence criteria before another change in speed occurs. We also see that varying speed trials have the greatest event time error; this is likely due to error that occurs as the algorithm learns a changed frequency (after already having met convergence criteria for a previously learned gait speed). Unlike the other gait types, the gait models for the varying speed trials are almost always in a learning state.

TABLE II: Manual Event Identification Performance with Gait Type. The top row shows the percentage of trials that converged; the middle and bottom rows show the convergence time and the event time error, respectively, in cycles.

	Total	Preferred	Walker	Asymmetric	Slow	Cane	Turn	Varying Speed
Trials Conv.	93% ($\frac{264}{285}$)	90% ($\frac{60}{67}$)	99% ($\frac{66}{67}$)	92% ($\frac{36}{39}$)	90% ($\frac{36}{40}$)	94% ($\frac{31}{33}$)	100% ($\frac{23}{23}$)	75% ($\frac{12}{16}$)
Conv. Time	5.46 ($\pm$2.38)	6.35 ($\pm$1.63)	5.39 ($\pm$1.81)	5.38 ($\pm$3.20)	5.06 ($\pm$3.62)	4.08 ($\pm$1.51)	6.32 ($\pm$1.76)	4.71 ($\pm$1.59)
Error	0.04 ($\pm$0.08)	0.01 ($\pm$0.01)	0.02 ($\pm$0.01)	0.04 ($\pm$0.05)	0.06 ($\pm$0.11)	0.05 ($\pm$0.06)	0.03 ($\pm$0.05)	0.27 ($\pm$0.22)

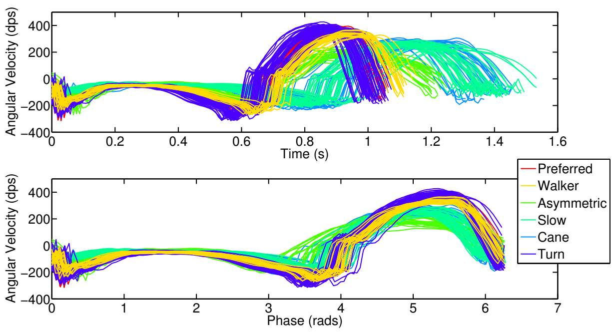

Fig. 3: Data Segments Plotted with Time (top) and Gait Model Phase (bottom). Although both panels show the same data, it is clear that events occurring in each gait cycle correspond more closely when aligned with the estimated phase rather than time (both between strides and between trials).

2) Segmentation: A segmentation algorithm was implemented that separates the data into segments, once criteria for convergence have been reached. Each segment is taken to be from one heel impact event to immediately before the next heel impact event. Data taken from one collection including all gait types except for varying speed is segmented and shown in Figure 3. The estimated phase variable allows the cycles, which are performed at various speeds, to be temporally aligned.

IV. Conclusions

The proposed method generates an accurate, individualized model of gait that can be used to estimate gait parameters and compared throughout patient rehabilitation to measure progress. The phase can also be used to accurately align multiple strides, providing both a measure of the gait parameters and their variability, a key measure of interest in gait analysis [3], [4].

Improved performance using this method is expected to be especially noticeable in pathological gait that contains atypical signal profiles' but maintains gait periodicity.

The conducted analysis assumes no prior knowledge about each individual. Implementation for real-world use would save learned model parameters unique to the individual, resulting in decreased convergence time.

In the future, we plan to apply the proposed approach to different sensor inputs and combinations of inputs, to patient data, and to detect a range of gait parameters.

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