Gait & Posture 46 (2016) 86–90

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Short Communication

Predicting ground contact events for a continuum of gait types: An application of targeted machine learning using principal component analysis

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ARTICLE INFO

Article history:
Received 23 October 2015
Received in revised form 5 February 2016
Accepted 25 February 2016

Keywords:
Foot strike
Event detection
Kinematics
Gait biomechanics

ABSTRACT

An ongoing challenge in the application of gait analysis to clinical settings is the standardized detection of temporal events, with unobtrusive and cost-effective equipment, for a wide range of gait types. The purpose of the current study was to investigate a targeted machine learning approach for the prediction of timing for foot strike (or initial contact) and toe-off, using only kinematics for walking, forefoot running, and heel-toe running. Data were categorized by gait type and split into a training set (~30%) and a validation set (~70%). A principal component analysis was performed, and separate linear models were trained and validated for foot strike and toe-off, using ground reaction force data as a gold-standard for event timing. Results indicate the model predicted both foot strike and toe-off timing to within 20 ms of the gold-standard for more than 95% of cases in walking and running gaits. The machine learning approach continues to provide robust timing predictions for clinical use, and may offer a flexible methodology to handle new events and gait types.

1. Introduction

In clinical settings, gait metrics are often calculated in relation to events like foot strike (initial contact) or toe-off. However, it can be difficult in such settings to obtain ground reaction force data, considered a gold standard for determining gait events.

There are many methodologies for determining timing of foot strike and toe-off from kinematics [1–10]. Unfortunately, this has created fragmentation in the literature, with a wide range of potential errors (up to 100 ms). Recently, a method was developed to predict timing of foot strike events during treadmill running [10] which demonstrated several advantages: no dependencies on specific markers, improved accuracy in the estimation of timing, and application to different foot strike techniques. The benefits of this approach could extend to treadmill walking, as well as the detection of toe-off, however the validity in these cases is unknown.

Therefore, the purpose of this study was to investigate a targeted machine learning approach, utilizing kinematics for the prediction of foot strike and toe-off during treadmill walking and running. Based on our previous work [10], it was hypothesized that a model trained on transient waveform features of sagittal-plane joint angular accelerations would be predictive of timing for foot strike and toe-off, in gaits including walking, forefoot running, and heel-toe running.

2. Methods

Kinematic and kinetic data during treadmill gait were queried from an existing database [11] on 186 subjects (mean ± stdev, age: 38.9 ± 10.9 yrs, height: 172.0 ± 9.2 cm, mass: 69.9 ± 12.5 kg, 108 female, walking speed: 1.13 ± 0.08 m/s, running speed: 2.65 ± 0.31 m/s). These individuals participated in clinical or research activities at the Running Injury Clinic and gave written informed consent. The institutional ethics review board gave approval for these data to be extracted from the database.

The methodology employed has been previously detailed [10]. Kinematic data were collected (200 Hz) using eight high-speed infrared video cameras (Vicon Motion Systems Ltd., Oxford,

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http://dx.doi.org/10.1016/j.gaitpost.2016.02.021
0966-6362/

UK), along with passive retro-reflective markers, and kinetic data were simultaneously collected (1000 Hz) using an instrumented, split-belt treadmill (Bertec Corporation, Columbus, OH).

After collection of a static neutral trial the subject was then asked to walk at 1.1 m/s while spanning the split belts, as naturally as possible. Following 2–5 min of acclimation, 60 s of walking data were collected. The treadmill was sped up to 2.7 m/s, or their preferred running speed, and after 2–5 min of acclimation, 60 s of running data were collected.

Following retrieval, data were further processed in MATLAB (The Mathworks, Natick, MA). Segment and joint kinematics were calculated using a singular value decomposition method [12] and a joint coordinate system [13]. Kinetic data were low-pass filtered (20 Hz cutoff), and down-sampled to match kinematic data. Gold-standard foot strike events were then determined using a rising-threshold of 10 N, and for toe-off, a falling-threshold of 10 N, both in the vertical force.

Completely novel models of ground contact dynamics for both foot strike and toe-off were created by first partitioning data into three groups. Walking ($n = 176$) trials were identified from instances of double support during gait. From the remaining running data, cases of heel-toe running ($n = 149$), and forefoot running ($n = 21$) were identified using the angle of the foot at gold-standard foot strike (foot sagittal angle relative to the horizontal <3 degrees of dorsiflexion).

For each of the three groups, a randomly selected subset of approximately 30% was chosen for a training set ($n = 104$ from $n = 346$), separately for both foot strike and toe-off detection. Kinematic data from each training set were analyzed similarly to a prior study [10], however, because data were newly randomized and partitioned, the models created were completely novel. Briefly, joint and foot angles were double-differentiated to obtain angular accelerations, and key frames were identified: for foot strike this peak foot dorsiflexion angular acceleration (FA_{pk}), and for toe-off this was peak foot plantarflexion angle (FP_{pk}). Kinematic data segments from each joint were defined using a window of 35 frames (175 ms) of data on either side of FA_{pk}, or 70 frames preceding FP_{pk}, and these were then chained together to form a row vector of 284 points. Separately for foot strike and toe-off, representative row vectors for each subject were stacked into an analysis matrix of 104×284 for input into a PCA, which produced a 284×104 matrix of coefficients, along with a 104×104 matrix of principal component (PC) scores. Frame delays between key frames and gold standard timings were calculated for each subject in the training set, and linear models were created using PC scores to predict frame delays.

After training, kinematics from each subject/gait in the 70% holdout validation sets for both foot strike and toe-off ($n = 244$ from $n = 346$) were similarly analyzed and projected into the same PC space as the original respective PCAs. The trained linear models were used to predict the timings of foot strike and toe-off relative to the key frames (FA_{pk} or FP_{pk}) for a minimum of ten consecutive footfalls, and compared with frame delays from gold-standard timings to determine errors. Median error was calculated to describe subject deviation from the models, while within-subject errors were calculated by subtracting subject median error from true errors for each footfall.

3. Results

Significant correlations were found between PC scores and frame delay in both foot strike and toe-off models during training (Fig. 1). In the foot strike model, scores from the second principal component (PC2) and frame delay were correlated, with all three gaits represented in the trend. In the toe-off model, the third principal component (PC3) scores and frame delay were correlated for running, while a tight clustering about a bias was observed for walking data.

For the foot strike model PC2 was loaded on foot and knee accelerations directly preceding FA_{pk}, and accounted for 10.4% of the original variance in the waveform data (Fig. 2). In the toe-off model PC3 demonstrated a strong correlation with frame delay for running, and was loaded on foot, ankle and knee accelerations ~175 ms prior to FP_{pk}, accounting for 8.1% of the original variance (Fig. 2).

For the foot strike model, more than 95% of median errors were within 20 ms across all gait types (95% PI (−20 ms, 20 ms), Fig. 3). Errors were lowest for walking, with 97% of the errors falling within 20 ms of the gold standard, and maximum error of 35 ms. Errors for heel-toe running were slightly greater, with 95% of the errors falling within 20 ms, and a maximum error of 35 ms. Errors for forefoot runners trended larger again, with 79% of errors falling within 20 ms, and the maximum error was 30 ms. Within-subject errors for touchdown detection demonstrated tighter intervals by comparison, with greater than 94% of all errors within 10 ms of the medians for each subject.

For the toe-off model, more than 95% of median errors were within 20 ms across all gait types (95% PI (−20, 20 ms), Fig. 3). Errors were lowest for walking with 99% of the errors falling within 20 ms of the gold standard, and a maximum error of 30 ms. Errors for heel-toe running trended higher with 92% falling within 20 ms, and a maximum error of 40 ms. For forefoot running, 77% of errors

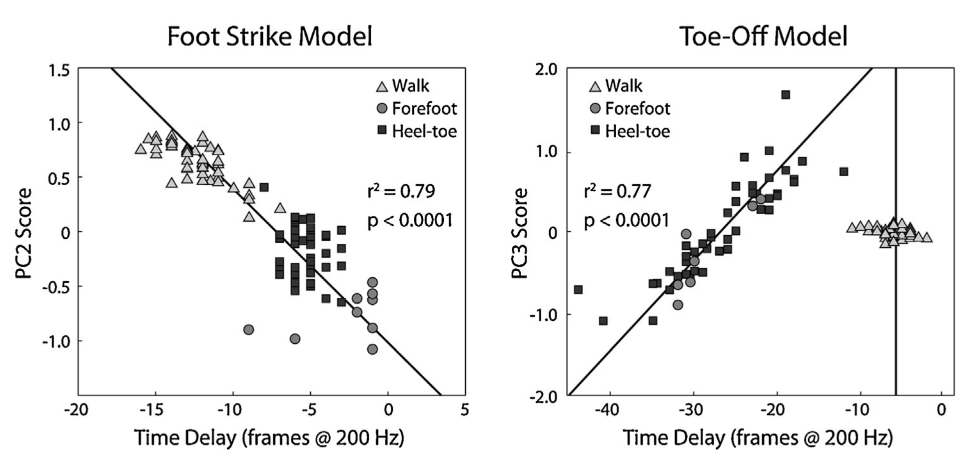

Fig. 1. The correlations observed in the training set for both models, between their respective principal components and the time delay observed between gold standard events and the respective key frame (FA_{pk} or FP_{pk}). Three groupings by gait type are shown: walking (triangles), heel-toe running (squares), and forefoot running (circles).