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Online gait event detection using a large force platform embedded in a treadmill

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ABSTRACT

Gait research and clinical gait training may benefit from movement-dependent event control, that is, technical applications in which events such as obstacle appearance or visual/acoustic cueing are (co)determined online on the basis of current gait properties. A prerequisite for successful gait-dependent event control is accurate online detection of gait events such as foot contact (FC) and foot off (FO). The objective of the present study was to assess the feasibility of online FC and FO detection using a single large force platform embedded in a treadmill. Center-of-pressure, total force output and kinematic data were recorded simultaneously in 12 healthy participants. Online FC and FO estimates and spatial and temporal gait parameters estimated from the force platform data—i.e., center-of-pressure profiles—were compared to offline kinematic counterparts, which served as the gold standard. Good correspondence was achieved between online FC detections using center-of-pressure profiles and those derived offline from kinematic data, whereas FO was detected 31 ms too late. A good relative and absolute agreement was achieved for both spatial and temporal gait parameters, which was improved further by applying more fine-grained FO estimation procedures using characteristic local minima in the total force output time series. These positive results suggest that the proposed system for gait-dependent event control may be successfully implemented in gait research as well as gait interventions in clinical practice.

1. Introduction

Experimental gait research and clinical gait training have become increasingly more sophisticated and often involve control of events in the actor-environment system, such as the introduction of obstacles or cues. Such events may be introduced either independently of the participant's gait (e.g., the presentation of obstacles may simply be controlled by a key-press by one of the experimenters (Pavol et al., 2001)) or on the basis of specific gait events such as foot contact (FC) and foot off (FO). The advantage of this latter type of movement-dependent event control is the high degree of control that it allows over the manipulations in question (Oudejans and Coolen, 2003). For example, the presentation of an obstacle can be timed precisely at early, mid, or late swing during walking (e.g., Pijnappels et al., 2004, 2005; Schillings et al., 1996) as the real-time manipulations in the environment are (co)determined by the ongoing movements of the participant.

For movement-dependent event control, gait registration equipment is required for the online identification of specific gait events, like FC or FO, from the collected gait data. The objective of the present study was to assess the feasibility of online FC and FO detection using a single large force platform embedded in a treadmill. In general, force platforms are particularly well-suited for gait event detection because FC and FO can be determined directly from thresholds in force recordings. However, threshold-based gait event detection becomes cumbersome when successive foot placements are not made on separate force platforms (Wearing et al., 2000). Participants are therefore often instructed to place their feet at certain positions, which may be difficult to accomplish in pathological gait (e.g., Dingwell and Davis, 1996), and/or may disturb the natural gait pattern due to visual targeting (Wearing et al., 2000). The key advantage of a single large force platform embedded in a treadmill is that gait is not constrained by restrictions on foot placement (see also Davis and Cavanagh, 1993). However, gait events like FC and FO cannot be directly determined from the force levels using threshold analyses because at least one foot is always placed on the force platform.

To address this issue, Davis and Cavanagh (1993) described an algorithm for decomposing registered total force output into individual left and right force profiles based on thresholds in the clear side-to-side movements of the measured center-of-pressure time series. The algorithm was based on assumptions on the definition of the start and end of stance phase from these side-to-side oscillations, which, unfortunately, were not validated.

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Dingwell and Davis (1996), using an instrumented treadmill with two force platforms in series, determined FC and FO based on arbitrarily chosen (i.e., by trial and error) thresholds and extrema in the derivative of the side-to-side center-of-pressure movements. More recently, Verkerke et al. (2005) validated the detection of FC gait events from center-of-pressure profiles collected with an instrumented treadmill equipped with separate force platforms on each side. Specifically, time instants of FC were based on thresholds in the forward velocity of the center-of-pressure trajectory and proved to be very accurate, as validated against concomitant force outputs close to zero of the associated platform (Verkerke et al., 2005). However, the detection of FO events was not specified and its validation was not addressed.

As valid and accurate online gait event detection is a prerequisite for successful movement-dependent event control, the present study compared online FC and FO estimates derived from a single large force platform to offline counterparts based on kinematic data (obtained with a 3D motion registration system), which served as the gold standard. The same was done for extracted gait parameters such as step length, step width, and step time.

2. Methods

Following informed consent, 12 healthy experienced treadmill walkers (7 males/5 females, 25–38 years of age, 163–194 cm in height, and 53–81 kg in weight) volunteered for the study that was endorsed by the local ethics committee and carried out in compliance with the Helsinki Declaration. After a familiarization period of at least 5-min of treadmill walking at different belt speeds, gait kinematics and force data were recorded synchronously at a sampling rate of 300 Hz for 80 s at a walking speed of 3.6 km/h.

Gait kinematics was recorded using an active-marker 3D motion registration system (OPTOTRAK 3020, Northern Digital Inc., Waterloo, Canada). Two small infrared-light emitting markers, placed on the heels of each shoe, were tracked by a rear-mounted OPTOTRAK camera system. FC and FO were determined by analyzing the kinematic data offline, which is a valid and reliable procedure that shows minimal error between the applied algorithm and raters on the one hand and among multiple raters on the other (Ghoussayni et al., 2004; Mickelborough et al., 2000; Wall and Crosbie, 1996). As illustrated in Fig. 1 (left panels), FC was determined by selecting the moment at which the vertical position of the heel marker reached its minimum, whereas FO was determined from local maxima in the vertical velocity component of the heel marker (Pijnappels et al., 2001; Roerdink et al., 2007). Furthermore, spatial and temporal gait parameters were determined on a step-to-step basis. Specifically, step (stride) time was quantified as the time interval between consecutive contralateral (ipsilateral) FC. Swing time was defined as the time interval between ipsilateral FO and FC. Stance time was defined as the time interval between ipsilateral FC and FO. Step length was derived by multiplying the belt speed by step times. Likewise, stride length was calculated by multiplying the belt speed by the stride time interval. Step width was quantified as the mean absolute mediolateral difference in the landing positions of consecutive contralateral FC.

Force data were registered after being transmitted through an analog signal conditioner (100-Hz low-pass filter) using a single large (1600×800 mm) force platform embedded in the treadmill (Bonte Technology/ForceLink, Culemborg, The Netherlands). Force data were first converted to center-of-pressure data, whose characteristic 'butterfly' pattern over time (see Fig. 1, right panel) facilitated the identification of gait events like FC and FO. As can be seen, during the single-support stance phase of the left leg, the center-of-pressure progresses backwards from the top to the bottom of the butterflies' left wing until the right foot strikes the force platform (FC_{right}). During the subsequent double-support stance phase, the center-of-pressure quickly moves forward and to the right (i.e., from the bottom of the left wing to the top of the right wing) until the left leg is cleared from the force platform (FO_{left}). Then the center-of-pressure moves backwards from the top to the bottom of the butterflies' right wing until heel strike of the left leg (FC_{left}), mediating a left-forward shift of the center-of-pressure until FO of the right leg (FO_{right}).

A custom online pattern recognition algorithm written in LabVIEW (National Instruments, Austin, US) was applied to detect these gait events in the center-of-pressure profile, i.e., left and right FC (FO) from posterior (anterior) center-of-pressure extrema contralateral to the side of interest (see Fig. 1, right panel). Specifically, current center-of-pressure sample values were compared continuously to a reference value, which was updated to the current value whenever the current value was greater (smaller) than the reference value for the detection of maxima (minima) in the center-of-pressure profile. If a lower (higher) value occurred, a counter was incremented by 1 until this counter met an adjustable peak criterion, which in our case was set to 30 samples, implying that 30 concurrent samples must be lower (higher) than the reference value to detect a maximum (minimum) in the center-of-pressure profile. Peak detection sensitivity is an important issue in online pattern recognition. Conservative peak detection sensitivity, as the one described above, is most accurate in that peak detection does not get trapped in local extrema. However, it goes at the expense of a temporal delay between peak identification and true peak occurrence. With the chosen peak detection sensitivity this delay is 0.1 s (i.e., 30 samples at a 300-Hz sampling frequency). Peak detection sensitivity might need to be adjusted for optimal peak detection, tailored to task (e.g., changes in walking velocity) and subject (e.g., pathological gait) constraints. For example, if a person walks very

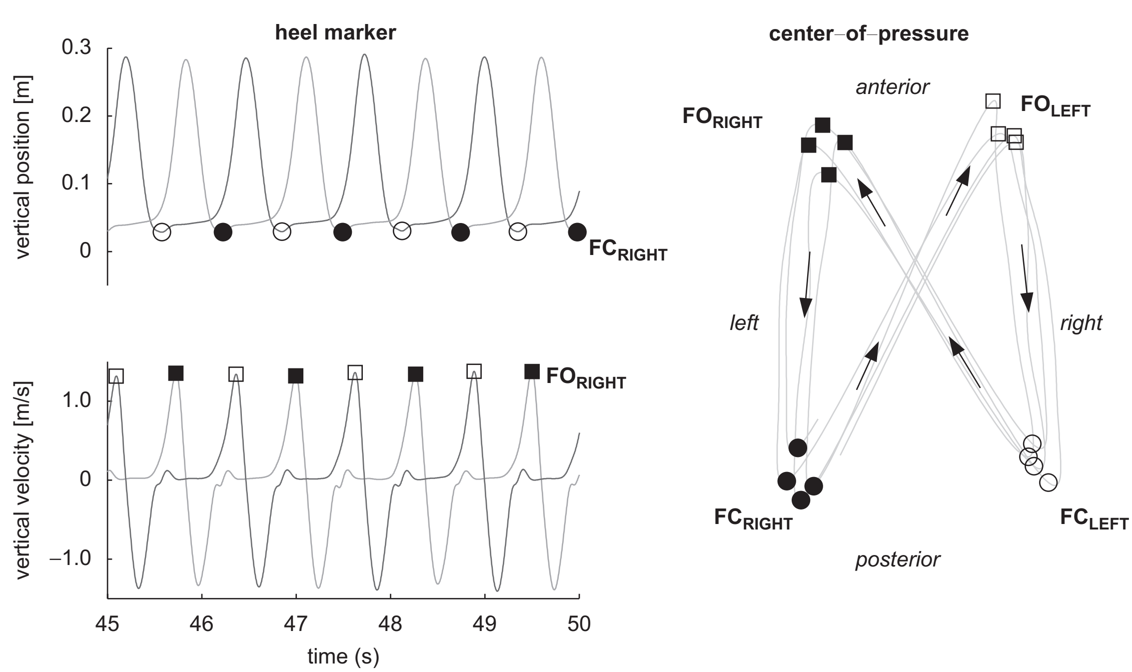

Fig. 1. Illustration of FC and FO detection times (represented by circles and squares, respectively) on the basis of heel marker kinematics (left panels) and center-of-pressure profiles (right panel). The direction of center-of-pressure progression during treadmill walking is indicated with the black arrows. Solid and open symbols represent right and left gait events, respectively.