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Short communication

A computational algorithm for classifying step and spin turns using pelvic center of mass trajectory and foot position

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ABSTRACT

Transient changes in direction during ambulation are typically performed using a step (outside) or spin (inside) turning strategy, often identified through subjective and time-consuming visual rating. Here, we present a computational, marker-based classification method utilizing pelvic center of mass (pCOM) trajectory and time-distance parameters to quantitatively identify turning strategy. Relative to visual evaluation by three independent raters, sensitivity, specificity, and overall accuracy of the pCOM-based classification method were evaluated for 90-degree turns performed by 3 separate populations (5 uninjured controls, 5 persons with transtibial amputation, and 5 persons with transfemoral amputation); each completed turns using two distinct cueing paradigms (i.e., laser-guided "freeform" and verbally-guided "forced" turns). Secondarily, we compared the pCOM-based turn classification method to adapted versions of two existing computational turn classifiers which utilize trunk and shank angular velocities (AV). Among 366 (of 486 total) turns with unanimous intra- and inter-rater agreement, the pCOM-based classification algorithm was 94.5% accurate, with 96.6% sensitivity (accuracy of spin turn classification), and 93.5% specificity (accuracy of step turn classification). The pCOM-based algorithm (vs. both AV-based methods) was more accurate (94.5% vs. 81.1–80.6%; $P < 0.001$) overall, as well as specifically in freeform (92.9 vs. 80.4–76.8%; $P < 0.003$) and forced (96.0 vs. 83.8–81.8%; $P < 0.001$) cueing, and among individuals with (92.4 vs. 80.2–78.8%; $P < 0.001$) and without (99.1 vs. 86.2–80.8%; $P < 0.001$) amputation. The pCOM-based algorithm provides an efficient and objective method to accurately classify 90-degree turning strategies using optical motion capture in a laboratory setting, and may be extended to various cueing paradigms and/or populations with altered gait.

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1. Introduction

Turns during ambulation are ubiquitous in daily life (Glaister et al., 2007). Several studies have therefore biomechanically evaluated turns using a variety of experimental methods; for example, with circular paths (Orendurff et al., 2006; Ventura et al., 2015) to understand "steady-state" turns, or orthogonal paths (Taylor et al., 2005), obstacles (Glaister et al., 2008), and other cues (Hase and Stein, 1999; Patla et al., 1991) to model "transient" turns (i.e., with more rapid changes in direction between 60° and 120°). The latter, generally referred to as "90°" turns, can be performed using two distinct turning strategies: (1) a step (outside) turn; a change in direction contralateral to the stance limb (e.g., left turn on the right leg), or (2) a spin (inside) turn; a pivot on the leg ipsilateral to the direction of turn (e.g., left turn on left leg). Biomechanical attributes of each strategy, together with the prevalence for a given turn type within a population, have been associated with risk of falling (Cumming and Klineberg, 1994) and risk for joint overloading after surgery (Wang and Zheng, 2010). Despite the utility of knowledge pertaining to an activity so common in daily life, the approach for identifying or classifying turns has evolved little.

Classification of transient turning strategies has almost exclusively relied on time-consuming visual ratings (i.e., identifying in real-time or evaluating a video recording; Hase and Stein, 1999; Patla et al., 1991; Taylor et al., 2005) which has the potential to introduce error/bias due to rater experience or interpretation. Interestingly, although numerous biomechanical attributes have been compared between each visually rated turn (Glaister et al.,

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2008; Taylor and Strike, 2009; Taylor et al., 2006; Wang and Zheng, 2010; Xu et al., 2004), only angular velocities of the trunk and shanks (collected using inertial measurement units [IMUs]) have been proposed for computationally categorizing these turning styles (Fino et al., 2015). Despite the recent increase in popularity of IMUs, especially for field-based measurements, optical motion capture remains the prevailing modality for comprehensive biomechanical analyses in a laboratory. Thus, here we present a novel computational method for transient 90° turn classification utilizing passive marker data. Secondarily, to understand whether the basis of the proposed algorithm provides a similar level of quality relative to existing methods, we evaluate the accuracy of the algorithm relative to the visually rated gold standard and modified angular velocity-based classifiers by applying all to planned ("forced") and unplanned ("freeform") turns, as well as within populations with transtibial (TTA) and transfemoral (TFA) amputations.

2. Methods

2.1. Participants

Five uninjured individuals ("controls"), five persons with unilateral TTA, and five persons with unilateral TFA completed the study (Table 1); all participants were servicemembers, and each provided informed consent to procedures approved by the Walter Reed National Military Medical Center Institutional Review Board. Uninjured controls reported no orthopaedic or neurological disorders, while persons with traumatic unilateral TTA or TFA could ambulate over even surfaces without an assistive device. All participants were also screened for brain injuries that may result in a functional impairment or inability to follow complex commands, as well as any visual impairment that would detract from the ability to follow a laser dot, and pain or discomfort (regardless of cause) greater than 4/10 on a Visual Analog Scale.

2.2. Study design and procedures

Each participant performed, at their self-selected pace, 90° turns cued using two distinct paradigms: (1) freeform [median (range) = 17 (6–19) turns/participant], and (2) forced [median (range) = 18 (6–20) turns/participant], resulting in a total of 236 and 250 events, respectively. Briefly, freeform trials were intended to simulate non-steady state gait representative of daily life (i.e., containing starts/stops, changes in direction, and in-line walking). For these, participants followed five distinct pseudorandom paths created by a laser dot as it moved along the floor surface (Laser Enabled Gait System; Mitre Corporation, Bedford, MA). The speed at which the laser moved was set according to each participant's self-selected walking speed (determined by timing an 80-m walk). 90° turns were extracted from the freeform trials for the purpose of the current study. In contrast, forced trials were intended to represent a more constrained, pre-planned turning event, involving repetitive bouts of straight-line walking (~12 ft) with verbal instructions to turn left or right as the participant approached a consistent point on the floor. In both freeform and forced trials, 70 reflective markers (modified Cleveland Clinic) were used for tracking (120 Hz) full-body kinematics using a 27-camera motion capture system (Vicon, Oxford, UK).

2.3. Data analyses

Pelvic center of mass (pCOM) position, trunk and shank angular velocities in the sagittal and transverse planes, as well as the relative timing and position of gait events (i.e., foot strike and foot off, calculated using foot position; Zeni et al., 2008) were computed and preprocessed in Visual3D (Version 5.02.27, C-Motion Inc., Germantown, MD). All marker trajectories were initially low pass filtered at 6 Hz using a 5th order Butterworth filter. Also note, each trial was cropped to include a brief inline entry (approximately 3 steps), 90° turn, and inline exit (approximately 3 steps) to minimize errors introduced by changes in direction unrelated to the turning event of interest. All subsequent analyses were performed in MATLAB (Release 2015a, The MathWorks, Inc., Natick, MA).

To determine whether the turn was a step (outside) or spin (inside) using the pCOM-based method, two lines of best fit were calculated for the first and last 100 frames of the pCOM trajectory (i.e., in-line periods before and after the turning event). Note, longer windows could be used, though our experimental design with freeform cueing precluded such an approach given the other gait events/changes in direction flanking each 90-degree turn of interest. The intersection of the two lines of best fit approximated the change in direction during a turn, hereafter referred to as the predicted pivot point. Then, midstance events corresponding to the time points midway between foot strike and foot off events of each leg were calculated for each step in the trial. The pivot foot was then determined by whichever foot was in midstance closest to the time when the pCOM was nearest to the predicted pivot point. The direction of turn was identified by cumulative trapezoidal integration of the axial angular velocity of the trunk; the sign of the resultant angle at 75% of the trial determined if the turn was to the left (positive angle) or right (negative angle). Together, the direction of turn and side of the predicted pivot foot defined the turn type: step (outside) = a left turn on the right foot or a right turn on the left foot, spin (inside) = a right turn on the right foot or a left turn on the left foot (Fig. 1).

Additionally, the pCOM-based method presented herein was also compared against two existing classifiers which use angular velocity (AV) as the basis of classification. These two AV-based methods (Fino et al., 2015) – while likely intended for field-based measurements and computed here using (filtered) marker data, and not unfiltered IMU data as originally described – consist of the: (1) peak method (PM) that sets the pivot foot as the shank with the lowest absolute sagittal angular velocity at the instant of maximum trunk axial angular velocity, and (2) the integrated method (IM), where the shank with the lowest absolute sagittal angular velocity at the time when the axial trunk angle exceeds 45° constitutes the pivot foot.

To compare the pCOM- and AV-based turn classification methods to the existing "gold standard", all turning events were first visually classified. For this, three independent raters classified all 486 turns as either a step or spin, three times each in a randomized order. Intra- and inter-rater reliability were assessed using Cohen's kappa (Cohen, 1960), adjusted for greater than two ratings within a set (Light, 1971) and qualitatively interpreted according to criteria set forth by Fleiss (1986): poor (0.00–0.39), fair (0.40–0.59), good (0.60–0.74), and excellent (0.75–1.00).

Intra- and inter-rater reliabilities were consistently excellent, ranging from 0.82–0.84 and 0.83–0.85, respectively. However, of the initial 486 turns (328/158 visually classified step/spin turns), 366 (75%) turns were rated with unanimous

Table 1
Participant demographics by level of injury (RTTA/LTTA = Right/Left Transtibial Amputation; RTFA = Right Transfemoral Amputation; RKD = Right Knee Disarticulation). Self-selected walking speeds (SSWS) are also indicated. Means and standard deviations (SD) for each group are provided (bolded), where applicable.

	Injury	Months since injury	Gender	Age (yr)	Stature (cm)	Mass (kg)	SSWS (m/s)
Controls	N/A	N/A	F	20	180.0	61.5	1.37
	N/A	N/A	M	28	169.0	88.4	1.37
	N/A	N/A	M	31	188.5	105.7	1.40
	N/A	N/A	M	28	185.0	72.6	1.30
	N/A	N/A	M	29	178.5	83.5	1.30
Control mean (SD)				**27 (4)**	**180.2 (7.4)**	**82.3 (16.7)**	**1.35 (0.05)**
TTA	RTTA	75.4	M	35	183.0	85.5	1.27
	LTTA	59.7	M	34	179.0	90.9	1.40
	RTTA	15.8	M	23	179.0	106.9	1.40
	RTTA	59.0	M	26	187.5	89.9	1.50
	RTTA	32.9	M	25	184.5	135.6	1.50
TTA mean (SD)		**48.6 (23.8)**		**29 (6)**	**182.6 (3.7)**	**101.8 (20.6)**	**1.41 (0.09)**
TFA	RTFA	5.5	M	24	170.0	71.4	1.08
	RTFA	54.0	M	26	178.5	94.1	1.20
	RTFA	47.8	M	27	186.0	96.2	1.40
	RKD	133.3	M	34	172.0	74.9	1.40
	RTFA	17.7	M	45	174.0	101.2	1.15
TFA mean (SD)		**51.7 (49.9)**		**31 (9)**	**176.1 (6.4)**	**87.6 (13.5)**	**1.25 (0.15)**

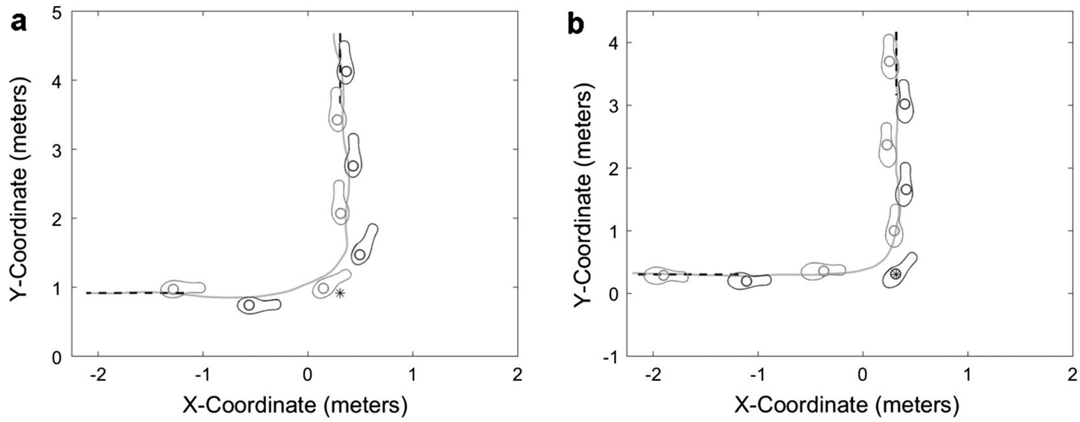

Fig. 1. Representative pelvic center of mass (pCOM) trajectory and bilateral foot positions (gray/black represents right/left, respectively) during a spin (a) and step (b) turn to the right. The predicted pivot point (⁎) and foot COM locations at midstance (○) are illustrated, with the black dashed line representing the sections of the pCOM extrapolated to predict pivot point.

agreement (248 step turns/188 spin turns). Only this subset of trials with unanimous intra- and inter-rater agreement was used to calculate sensitivity [true spin/(true spin + false step)], specificity [true step/(true step + false spin), and overall accuracy [(true step + true spin)/total] of both the pCOM- and AV-based classification methods. Each of these was computed by cueing paradigm and subject populations, with additional comparisons between pivot leg among persons with lower limb amputation (prosthetic vs. intact). Performance of the pCOM-based method and each AV method (i.e., IM and PM, independently) was also assessed using a binomial test (*cf.* Salzberg, 1997), which evaluates differences in the frequency of accurate classification between the methods relative to the gold standard (unanimous visual rating in this particular case); P values less than 0.004 indicate statistical significance (Bonferroni correction for 12 total comparisons).

3. Results

Overall, the pCOM-based method was 94.5% accurate relative to visual rating, with 96.6% sensitivity (ability to classify spin turns in agreement with visual rating) and 93.5% specificity (ability to classify step turns in agreement with visual rating). Accuracies tended to be lower in freeform (92.9%) vs. forced (96.0%) trials, as well as lower among persons with (92.4%) vs. without (99.1%) amputation (Table 2).

Both the PM/IM methods performed similarly, with 81.1/80.6% accuracy, 82.2/89.0% sensitivity, and 80.6/76.6% specificity relative to visual rating. Both AV-based methods were generally less accurate in freeform vs. forced turns (80.4/76.8% vs. 81.8/83.8%, respectively), and less accurate for persons with (78.8/80.2%) vs. without (86.2/80.8%) amputation (Table 2).

Among persons with amputation, specifically, overall (both forced and freeform combined) accuracies for the pCOM/PM/IM methods for turns executed on the prosthetic limb were 89.9%/78.9%/81.7%; respective values for turns on the intact limb were 94.3%/78.7%/80.1% (Table 3).

The pCOM method agreed with unanimous visual ratings more frequently than the PM and IM methods overall ($P < 0.001$), and within subgroups of freeform trials ($P < 0.003$), forced trials ($P < 0.001$), and persons with vs. without amputation ($P < 0.003$).

4. Discussion

Relative to the gold standard (visual rating), the pCOM-based classification method was accurate for both freeform and forced turns, as well as for participants with and without amputation. Also, although the original AV-based methods were designed for field-based measurements with unfiltered IMU data, the higher sensitivity, specificity, and overall accuracy, the pCOM- vs. AV-based classification algorithms suggest the pCOM is an effective basis for classifying turns using passive marker data, and an improvement over existing approaches in this scenario.

Table 2
Sensitivity, specificity, and overall accuracy of the pelvic center of mass (pCOM)-based and two angular velocity (AV)-based methods (PM = Peak Method, IM = Integrated Method), designated for freeform and forced turning trials, by level of injury (TTA = Transtibial Amputation; TFA = Transfemoral Amputation). Sensitivity and specificity represent the accuracies of spin and step turn classification, respectively, relative to turns rated unanimously by visual raters.

			Sensitivity (%)	Specificity (%)	Accuracy (%)
COM-based	Controls	Freeform	94.1	100.0	98.2
		Forced	100.0	100.0	100.0
	TTA	Freeform	100.0	86.7	89.1
		Forced	95.5	93.6	94.2
	TFA	Freeform	94.7	89.7	91.4
		Forced	96.9	91.7	94.1
AV-based (PM)	Controls	Freeform	88.2	84.2	85.5
		Forced	83.3	88.4	86.9
	TTA	Freeform	40.0	88.9	80.0
		Forced	90.9	72.3	78.3
	TFA	Freeform	84.2	71.8	75.9
		Forced	84.4	77.8	80.9
AV-based (IM)	Controls	Freeform	76.5	73.7	74.5
		Forced	88.9	83.7	85.2
	TTA	Freeform	90.0	68.9	72.7
		Forced	95.5	66.0	75.4
	TFA	Freeform	89.5	79.5	82.8
		Forced	90.6	91.7	91.2

Table 3
Sensitivity, specificity, and overall accuracy of the pelvic center of mass (pCOM)-based and two angular velocity (AV)-based methods (PM = Peak Method, IM = Integrated Method) among persons with lower limb amputation by pivot leg. Sensitivity and specificity represent the accuracies of spin and step turn classification, respectively, relative to unanimous visual ratings.

			Sensitivity (%)	Specificity (%)	Accuracy (%)
COM-based	Intact	Freeform	94.4	90.5	91.7
		Forced	100.0	93.8	96.3
	Prosthetic	Freeform	100.0	85.7	88.7
		Forced	90.5	91.4	91.1
AV-based (PM)	Intact	Freeform	72.2	78.6	76.7
		Forced	97.0	68.8	80.2
	Prosthetic	Freeform	63.6	83.3	79.2
		Forced	71.4	82.9	78.6
AV-based (IM)	Intact	Freeform	88.9	69.0	75.0
		Forced	97.0	75.0	84.0
	Prosthetic	Freeform	90.9	78.6	81.1
		Forced	85.7	80.0	82.1

Initial iterations of the pCOM-based method sought to utilize previously reported biomechanical metrics demonstrating relative differences between step and spin turns, both kinetic (e.g., knee moments and ground reaction forces; Taylor et al., 2005) and kinematic (e.g., tibial torsion; Wang and Zheng, 2010). However, such bases for turn categorization may be suboptimal choices for development of a widely applicable algorithm. For example, a classifier based on kinetic metrics would be limited by the necessity of clean foot strikes on a force platform. Full kinematic traces over the course of a turn also may not be robust to compensatory adaptations in different populations and environments, while single extracted time points (i.e., extrema) may not provide the requisite accuracy. Although the pCOM method required segmentation of turns, and is therefore limited to a post-processing paradigm, pelvic COM trajectory provided a consistent, intuitive framework that was resistant to variations in trunk angle; a confounding factor in laser guided freeform trials (i.e., from a more downward-directed gaze).

Both gait kinematics and kinetics are affected by turn methodology (i.e., circular/steady-state vs. orthogonal/transient turns; Orendurff et al., 2006), gait velocity (Lelas et al., 2003), and gait pathology (Bae et al., 2007; Bateni and Olney, 2002). Thus, transient turns performed by participants with varying levels of injury and in a freeform, laser-cued environment were expected to challenge the pCOM-based algorithm. Consistently lower overall accuracies in rating freeform vs. forced turns suggest cueing paradigm did influence the biomechanical metrics used here, even within transient turning strategies. Although the pCOM-based method was more accurate relative to AV-based methods in classifying turns executed by both persons with and without lower limb amputation, the 6.7% lower accuracy in pCOM classification of turns among persons with vs. without amputation suggest that some compensatory mechanism during turns may confound pCOM-based algorithm performance. Future work may explore which biomechanical deviations are drivers of this lower accuracy, with potential starting points being deviations in trunk angular velocity (Goujon-Pillet et al., 2008; Taylor and Strike, 2009), ground reaction forces, and lower extremity joint moments (Segal et al., 2011; Ventura et al., 2011) - all metrics affected by adaptations persons with lower limb amputation use during turns.

Understanding sources of error in pCOM-based classification between populations and cueing paradigms may guide the development of subsequent classifiers through selection of bases robust to biomechanical compensations. Additionally, more advanced pattern recognition techniques (e.g., linear discriminant analysis or artificial neural networks) may identify multi-step strategies beyond step and spin, such as stutter stepping. The relatively young servicemembers with traumatic amputation assessed in this study were active and high functioning and, thus, may limit the generalizability of results to those with other amputation etiologies or gait deficiencies.

Despite these limitations, the pCOM-based classification algorithm presented here was effective and accurate for transient 90-degree turns executed in both forced and freeform cueing paradigms, as well as in populations demonstrating marked biomechanical alterations. The pCOM-based algorithm can be implemented in place of subjective and time-consuming visual ratings, and concurrently provides a platform for classification and biomechanical analyses of transient turns performed using optical motion capture within a laboratory setting.

Conflicts of interest

The authors declare no financial or personal relationships with other persons or organizations that might inappropriately influence our work presented herein. The views expressed in this article are those of the authors and do not necessarily reflect the official policies or position of the U.S. Departments of Defense, Veterans Affairs, the Army, or the Navy.

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References

Bae, T.S., Choi, K., Hong, D., Mun, M., 2007. Dynamic analysis of above-knee amputee gait. Clin. Biomech. 22, 557–566.
Bateni, H., Olney, S.J., 2002. Kinematic and kinetic variations of below-knee amputee gait. JPO J. Prosthetics Orthot. 14, 2–10.
Cohen, J., 1960. Kappa: coefficient of concordance. Educ. Psych. Meas. 20, 37.
Cumming, R.G., Klineberg, R.J., 1994. Fall frequency and characteristics and the risk of hip fractures. J. Am. Geriatr. Soc. 42, 774–778.
Fino, P.C., Frames, C.W., Lockhart, T.E., 2015. Classifying step and spin turns using wireless gyroscopes and implications for fall risk assessments. Sensors (Switzerland) 15, 10676–10685.
Fleiss, J.L., 1986. Reliability of measurement. Des. Anal. Clin. Exp., 1–32
Glaister, B.C., Bernatz, G.C., Klute, G.K., Orendurff, M.S., 2007. Video task analysis of turning during activities of daily living. Gait Posture 25, 289–294.
Glaister, B.C., Orendurff, M.S., Schoen, J.A., Bernatz, G.C., Klute, G.K., 2008. Ground reaction forces and impulses during a transient turning maneuver. J. Biomech. 41, 3090–3093.

Goujon-Pillet, H., Sapin, E., Fodé, P., Lavaste, F., 2008. Three-dimensional motions of trunk and pelvis during transfemoral amputee gait. Arch. Phys. Med. Rehabil. 89, 87–94.
Hase, K., Stein, R.B., 1999. Turning strategies during human walking. J. Neurophysiol. 81, 2914–2922.
Lelas, J.L., Merriman, G.J., Riley, P.O., Kerrigan, D.C., 2003. Predicting peak kinematic and kinetic parameters from gait speed. Gait Posture 17, 106–112.
Light, R.J., 1971. Measures of response agreement for qualitative data: Some generalizations and alternatives. Psychol. Bull. 76, 365–377.
Orendurff, M.S., Segal, A.D., Berge, J.S., Flick, K.C., Spanier, D., Klute, G.K., 2006. The kinematics and kinetics of turning: limb asymmetries associated with walking a circular path. Gait Posture 23, 106–111.
Patla, A.E., Prentice, S.D., Robinson, C., Neufeld, J., 1991. Visual control of locomotion: strategies for changing direction and for going over obstacles. J. Exp. Psychol. Hum. Percept. Perform. 17, 603–634.
Salzberg, S., 1997. On comparing classifiers: pitfalls to avoid and a recommended approach. Data Min. Knowl. Discov. 328, 317–328.
Segal, A.D., Orendurff, M.S., Czerniecki, J.M., Schoen, J., Klute, G.K., 2011. Comparison of transtibial amputee and non-amputee biomechanics during a common turning task. Gait Posture 33, 41–47.
Taylor, M., Strike, S., 2009. Strategies used by transtibial amputees to suddenly change direction whilst walking. Gait Posture 30, S85.
Taylor, M.J.D., Dabnichki, P., Strike, S.C., 2005. A three-dimensional biomechanical comparison between turning strategies during the stance phase of walking. Hum. Mov. Sci. 24, 558–573.
Taylor, M.J.D., Strike, S.C., Dabnichki, P., 2006. Strategies used for unconstrained direction change during walking. Percept. Mot. Ski. 102, 576–588.
Ventura, J.D., Klute, G.K., Neptune, R.R., 2015. Individual muscle contributions to circular turning mechanics. J. Biomech. 48, 1067–1074.
Ventura, J.D., Segal, A.D., Klute, G.K., Neptune, R.R., 2011. Compensatory mechanisms of transtibial amputees during circular turning. Gait Posture 34, 307–312.
Wang, H., Zheng, N., 2010. Knee rotation and loading during spin and step turn. Int. J. Sports Med. 31, 742–746.
Xu, D., Carlton, L.G., Rosengren, K.S., 2004. Anticipatory postural adjustments for altering direction during walking. J. Mot. Behav. 36, 316–326.
Zeni, J.A., Richards, J.G., Higginson, J.S., 2008. Two simple methods for determining gait events during treadmill and overground walking using kinematic data. Gait Posture 27, 710–714.