Accuracy between optical and inertial motion capture systems for assessing trunk speed during preferred gait and transition periods

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ACCURACY BETWEEN OPTICAL AND INERTIAL MOTION CAPTURE SYSTEMS FOR ASSESSING TRUNK SPEED DURING PREFERRED GAIT AND TRANSITION PERIODS

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ABSTRACT

Motion capture through inertial sensors is becoming popular, but its accuracy to describe kinematics during changes in walking speed is unknown. The aim of this study was to determine the accuracy of trunk speed extracted using an inertial motion system compared to a gold standard optical motion system, during steady walking and stationary periods. Eleven participants walked on pre-established paths marked on the floor. Between each lap, a 1-second stationary transition period at the initial position was included prior to the next lap. Resultant trunk speed during the walking and transition periods were extracted from an inertial (240 Hz sampling rate) and an optical system (120 Hz sampling rate) to calculate the agreement (Pearson's correlation coefficient) and relative root mean square errors between both systems. The agreement for the resultant trunk speed between the inertial system and the optical system was strong ($0.67 < r \leq 0.9$) for both walking and transition periods. Moreover, relative root mean square error during the transition periods was greater in comparison to the walking periods (>40% across all paths). It was concluded that trunk speed extracted from inertial systems have fair accuracy during walking, but the accuracy was reduced in the transition periods.

Key-words: inertial sensors, validation, kinematics, biomechanics, walking

INTRODUCTION

Technologies to record and analyse human movement are divided in optical and non-optical systems. Optical motion capture systems (OMC) consist of recording the displacement of passive or active markers using multiple cameras overlapping each other's field of view (Robertson, Caldwell, Hamill, Kamen, & Whittlesey, 2014). Optical systems can be used outside of laboratory settings, but portability issues limit its use in the field (Thies et al., 2007). Non-optical motion capture systems measure motion based on the relative position of different segments. Inertial motion capture systems (IMC) consist of a group of inertial measurement units (IMUs) to acquire data from accelerometers, gyroscopes and magnetometers. Post-processing using fusion algorithms can provide segment and joint kinematic parameters. In case of tracking object/segment displacement, it is advantageous to use multiple IMUs to reduce measurement errors and improve accuracy (Bancroft & Lachapelle, 2011; O'Reilly, Whelan, Ward, Delahunt, & Caulfield, 2017). Inertial systems have been considered a promising alternative to conduct motion analysis due to lower cost, simplified experimental setup and a vast array of possibilities to acquire data during natural conditions (Floor-Westerdijk, Schepers, Veltink, van Asseldonk, & Buurke, 2012; Karatsidis et al., 2016; Laudanski, Yang, & Li, 2011). However, data acquired from IMCs are susceptible to magnetic interference and drift with respect to time when differentiating acceleration to obtain position (Damgrave & Lutters, 2009; de Vries, Veeger, Baten, & van der Helm, 2009). Therefore, assuring the accuracy of inertial motion capture systems to investigate human motion is essential to the future applications of this technology.

The growing interest in the use of IMCs has led researchers to assess the accuracy of such systems. Laudanski and co-workers (Laudanski et al., 2011) have found acceptable estimates of walking speed using IMUs placed on the shank and foot in case of natural walking patterns, but not for modified patterns such as toe-out walking. Morrow et al. (2016) found acceptable accuracy for neck, trunk and shoulder angles calculated using IMCs, but accuracy should be interpreted as protocol specific. In addition, strong and excellent agreement between predicted and actual measures have been found when inertial systems were used to predict ground reaction forces (Karatsidis et al., 2016). These previous reports suggest that inertial motion capture systems are accurate for their specific purposes.

Tracking the speed of an object and/or individual in space can be relevant for many research fields such as sports, ergonomics and medicine (Laudanski et al., 2011), but the accuracy of emerging motion capture technologies must be assured (Floor-Westerdijk et al., 2012; Karatsidis et al., 2016). Previous studies have found acceptable/good accuracy when determining gait parameters such as step length (Zijlstra & Hof, 2003), centre of mass displacement (Floor-Westerdijk et al., 2012), and walking speed using accelerometers (Aminian, Robert, Jequier, & Schutz, 1995; Song, Shin, Kim, Lee, & Lee, 2007; Zijlstra & Hof, 2003). It is noteworthy that all these previously cited studies base their experimental protocols on treadmill walking, or preferred overground walking speed. Therefore, the accuracy of inertial sensors in these studies has not been challenged by changes in walking speed or stationary periods, which frequently occur in our daily.

Previous studies have shown that the accuracy of IMC measurements can be reduced when complex motion or changes in direction occur (Godwin, Agnew, & Stevenson, 2009; Robert-Lachaine, Mecheri, Larue, & Plamondon, 2017a). Therefore, understanding the accuracy of inertial sensors to detect periods of stationarity and changes in direction in freely moving humans is relevant in several contexts, such as: defining the displacement and movement pattern of workers in factories (where global position systems [GPS] may not work), track the displacement, speed and stationary periods of patients undergoing rehabilitation in hospitals, clinics or at home (Beyea, McGibbon, Sexton, Noble, & O'Connell, 2017; Robert-Lachaine, Mecheri, Larue, & Plamondon, 2017a; Robert-Lachaine et al., 2017b; Zhou & Hu, 2007). The use of inertial sensors can help extracting information that has been neglected in clinical biomechanics, such as the sub-phases of a time to up-and-go test (Beyea et al., 2017). However, in case of insufficient accuracy, the predictions made from inertial sensors might provide misleading data and erroneous assumptions. In this sense, there is a lack of studies attesting the accuracy of IMCs in retrieving accurate segment position and velocity during fluctuations in walking speed or stationary periods.

The aim of this study was to determine the accuracy of an IMC to determine trunk segment three-dimensional position and resultant speed in relation to a gold standard OMC in two conditions: (1) normal walking at preferred speed and (2) transition periods consisting of deceleration, standing and return to walk. It was hypothesised that the accuracy of the measures from IMCs during normal walking would be high. However, the accuracy during transition periods would be poor, as the acquisition based on accelerations for the inertial sensors can be compromised in the transition periods.

METHODS

Participants

Eleven adults (24±1 years, height 180±13 cm, body mass 82±14 kg) volunteered to participate in this experiment. The exclusion criteria to participate in this experiment was any existent musculoskeletal disorder that could impair walking performance (i.e., lower limb muscle strain, tendinisis, ostearthrisis, etc.). The experiment was performed in accordance with the ethical guidelines of The North Denmark Region Committee on Health Research Ethics.

Experimental design

In a single session, participants were initially acclimatised to the lab environment and experimental setup. The task consisted of performing walking at self selected speed on three pre-established pathways marked on the floor: 1 x 1 m path, 2 x 2 m path and 2 x 3 m path located in the central area of a 12 x 8 m room. The order of the paths was randomised for each participant. For each path, participants were asked to perform four laps clockwise while briefly stopping for one second at the initial position, characterising a transitory period of deceleration and acceleration from and to a stationary position (DEC/ACC, Figure 1A). The DEC/ACC periods were included to provide data containing substantial changes in segment acceleration and a brief stationary period, contrasting to the rather stable segment displacement during normal walking. This procedure was repeated three times for each path, totalling 12 laps and nine DEC/ACC periods for each path. A rest interval of 5 minutes was provided between each set of recordings. During the walking tasks, motion data was recorded from an IMC and an OMC simultaneously, the latter being considered the gold standard for the purposes of this investigation.

INSERT FIGURE 1 HERE

Inertial motion capture system

An IMC system (Xsens MVN Link, Xsens Technologies BV, Enschede, The Netherlands) and its respective software (Xsens MVN Studio version 4.2.4, Enschede, The Netherlands) were used to record full-body kinematics at a sampling rate of 240 Hz. The IMC consisted of 17 IMU modules (25 x 35 x 8 mm, 30 g) mounted on a tight-fitting Lycra suit containing pre-defined locations for sensor placement (Figure 2A). The IMUs were placed bilaterally on the following locations: shoulder, arm, forearm, hand, thigh, shank and foot. In addition, IMUs were placed on the head (using a headband), on the chest and on the sacrum. The manufacturer's sensor calibration procedure was followed by asking participants to assume different body poses such as N-pose (quiet standing with arms alongside the body) and T-pose (quiet standing with arms abducted 90º and horizontally aligned in the frontal plane). This calibration procedure assured the different IMUs were correctly representing the body's segments in the three-dimensional space. The manufacturer's recommendations to avoid sources of electromagnetic fields were followed to assure the quality of the acquired data.

INSERT FIGURE 2 HERE

Standard optical motion capture system

An eight infrared high-speed cameras system (Oqus 300 series, Qualisys AB, Gothenburg, Sweden) OMC was used to capture 7 retro-reflective markers that defined the participants' trunk segment. The markers (12 mm diameter, Qualisys AB, Gothenburg, Sweden) were placed on top of the IMC Lycra suit in the following bone landmarks: left and right acromium, left and right anterior superior iliac spine, seventh cervical vertebrae, xiphoid process of the sternum and manubrium process of the sternum (Figure 2B). Considering that both the markers and the Lycra suit could move in relation to the bone landmarks, the marker and suit were periodically checked to assure the correct placement throughout the experiment. The sampling frequency of the OMC was set at 120 Hz. A synchronisation device (Xsens Sync station, Enschede, The Netherlands) was used to synchronise the IMC and OMC. The data from the IMC were resampled to 120 Hz to match the OMC sampling frequency.

Data processing

For the IMC, the orientation of each IMU was obtained by fusing accelerometer, gyroscope and magnetometer signals using an extended Kalman filter embedded in the IMC recording software (Roetenberg, Luinge, Baten, & Veltink, 2005). The IMC software computed the three-dimensional position vectors for all sensors. Moreover, the IMC software partitioned the trunk kinematic data into four different segments (L3, L5, T8 and T12 vertebrae), and generated position vectors for each of these spine levels. The position vectors from these spine levels were low-pass filtered (6 Hz, second-order Butterworth zero-phase). A preliminary analysis using trunk position data from the sensor located on the chest did not reveal significant differences when compared to averaged position data extracted from all four spine levels (L3, L5, T8 and T12 vertebrae). Therefore, the trunk position in each direction was defined as the average across all four spine levels for each time frame. For the OMC, the marker position vectors were low-pass filtered (6 Hz, second-order Butterworth zero-phase) and processed with Visual 3D software (Visual3D V6 Professional, C-Motion, Germantown, USA) to calculate the trunk centre of mass position vectors. The trunk position vectors from IMC and the trunk centre of mass position vectors from OMC were derived to generate velocity vectors. The resultant trunk speed was subsequently defined as:

$$S(i) = \sqrt{x(i)^2 + y(i)^2 + y(i)^2}$$

where for each time frame (i), S was the resultant speed from the velocity vectors in the anterior-posterior (x), medial-lateral (y) and vertical directions (z). Data was analysed using custom scripts programmed in MATLAB® (R2015b, Mathworks Inc., Natick, MA USA).

Data analysis

The trunk resultant speed from OMC was used to define the walking periods (e.g., individual laps) and the DEC/ACC periods. The walking periods were segmented when the trunk resultant speed was > 0.2 m/s, and the DEC/ACC periods were defined as the periods in which speed was <= 0.2 m/s (Figure 1B). The total trunk displacement was computed from the beginning of the first lap to the end of the fourth lap in each of the three sets of recordings for each path. The segmentation extracted from the OMC data was used to segment the IMC data. Regarding the segmented walking and DEC/ACC periods, the average trunk speed was determined as the average across each trial, and subsequently averaged across all trials for each participant.

Statistical analysis

The Statistical Package for the Social Sciences (IBM SPSS Inc. Version 23.0, Chicago, IL, USA) was used for statistical analysis. The normality of the dependent variables (total distances, walking speed was assessed using Shapiro-Wilk tests. To evaluate the accuracy of IMC total trunk displacement and resultant trunk speed for the walking and DEC/ACC periods, the relative root mean square error (rRMSE) in relation to data from the OMC were calculated, as defined by Ren et al. (Ren, Jones, & Howard, 2008). In addition, the agreement between the total trunk displacement from both systems was derived from Pearson's correlation coefficients, which were categorised as weak ($r \leq 0.35$), moderate ($0.35 < r \leq 0.67$), strong ($0.67 < r \leq 0.9$) and excellent ($r > 0.9$), according to previous studies (Karatsidis et al., 2016; Taylor, 1990). The effects of different path lengths (1 x 1 *vs* 2 x 2 *vs* 2 x 3) and motion capture systems (IMC *vs* OMC) on the resultant trunk speed were assessed by using 2-way ANOVA for repeated measures. The significance level was set at $p<0.05$.

RESULTS

The total distances tracked during the sets of four laps including the DEC/ACC periods presented low rRMSE (<15%) for the 2 x 2 and 2 x 3 paths in the anterior-posterior and medial-lateral directions (Table 1). However, the rRMSE was higher (32±24%) for the 1 x 1 path in these movement directions. In addition, the rRMSE for the vertical direction was high regardless the path length (117±79% across all paths). But there was a trend to reduced rRMSE for the longer paths (Table 1). The agreement between the IMC and OMC measurements was excellent ($r > 0.9$) for both the anterior-posterior and medial-lateral directions across all paths. For the vertical direction, the agreement was strong for the 1 x 1 path ($0.67 < r \leq 0.9$), and it was moderate ($0.35 < r \leq 0.67$) for the 2 x 2 and 2 x 3 paths.

INSERT TABLE 1 HERE

Resultant trunk speed

There was no significant main effect of the different paths on the DEC/ACC speed (Figure 2, $p>0.05$). In contrast, there was a main effect of systems ($F = 20.20$; $p = 0.0006$; $\eta p^2 = 0.669$) demonstrating that the resultant trunk speed calculated from the IMC was greater in comparison to the speed calculated from the OMC. Regarding walking speed, there was a main effect of paths ($F = 134.32$; $p = 0.00002$; $\eta p^2 = 0.968$) demonstrating that the shorter the path, the slower the resultant trunk speed. Post-hoc test revealed significant differences among all paths (Figure 2). There was no main effect of system for the walking speed ($p>0.05$). In addition, there were no interaction effects for both walking and DEC/ACC speed ($p>0.05$).

INSERT FIGURE 2 HERE

For the walking trials, there was a tendency for longer periods of recording as a function of longer distances to walk in a lap (Table 2), whereas the duration of the DEC/ACC periods ranged between 1.5-2 s across all paths. The agreement for the resultant trunk speed between IMC and OMC was strong for both walking and DEC/ACC periods across all paths. The rRMSE of the resultant trunk speed during the walking periods was 19.90±7.82% across all paths (Table 2). In contrast, the rRMSE during the DEC/ACC periods were consistently greater (51.16±14.88% across all paths) when qualitatively compared to the walking rRMSE.

INSERT TABLE 2 HERE

DISCUSSION AND IMPLICATIONS

The main findings of the present study were that IMCs can retrieve similar total distances (in the anterior-posterior and medial-lateral directions) and resultant speed in comparison to a gold standard OMC during walking. However, there were overestimations of the speed computed from the IMC during transition periods of deceleration and acceleration from and to stationary positions, when compared to the gold standard OMC. In practice, these results suggest that inertial sensors can be used for defining segment displacement when speed is constant, but acceleration/deceleration patterns from and to stationary positions may lack accuracy.

In the present study, there was a strong agreement between IMC and OMC for the total trunk centre of mass distances in the anterior-posterior and medial-lateral directions, but it was moderate in the vertical direction. A previous study found high accuracy for the vertical centre of mass displacement calculated from a inertial sensor located on the sacrum and OMC (Floor-Westerdijk, Schepers, Veltink, van Asseldonk, & Buurke, 2012), but accuracy was moderate for the anterior-posterior and medial-lateral directions. The authors argued that the lower accuracy for the anterior-posterior and medial-lateral directions were caused by the influence of pelvic rotations on the inertial recordings. Our results do not corroborate this study, and the contrasting evidence might be related to the different data acquisition methods. The present study recorded only trunk kinematics using OMC, and full-body kinematics using IMC, whereas the referenced study recorded full-body OMC and one inertial sensor on the sacrum. The trunk movement substantially contributed to the centre of mass calculation (Floor-Westerdijk et al., 2012), and the estimation of the centre of mass displacement using a single sacral markers can lead to poor precision (Gard, Miff, & Kuo, 2004). Therefore, estimating centre of mass kinematics using a single inertial sensor might not be optimal, but the lack of consistency across studies compromises further comparisons. In the present study, the displacement of four trunk segments form the IMC were used to describe the trunk displacement and speed, which were extracted from the manufacturer's fusion algorithm. Future studies addressing the accuracy of IMC systems should focus on standardising recording methods, to facilitate comparison to previous validation studies.

The validity of IMC has been investigated with fair estimates for centre of mass position (Floor-Westerdijk et al., 2012), lower limb joint angles in the sagittal plane (Zhang, Novak, Brouwer, & Li, 2013) and ground reaction forces prediction during walking (Karatsidis et al., 2016). Laudanski et al. (2011) found rRMSE between 5% and 7.5% for walking speed computed using inertial sensors located in the shank and foot, but the comparison was performed between a pre-established treadmill speed and the inertial sensor's speed. In the present study, it was found a greater rRMSE for the speed measured during walking (~17%, across all paths) compared to Laudanski and co-worker's study (up to 7.5%). However, direct comparison between studies need caution, as the study of Laudanski and co-workers did not use a reference kinematic measurement for comparison.

There was a remarkable rRMSE for the trunk speed measured during the DEC/ACC periods (~51%, across all paths), which was substantially greater than the error found during walking (~17%). Previous studies have reported greater measurement errors for IMC when participants performed upper limb movements with increased duration and complexity (Godwin et al., 2009; Robert-Lachaine et al., 2017b). In addition, Godwin and Stevenson (2009) reported that the greater errors of their experiment occurred during changes in movement direction. This phenomenon has been also observed by previous studies using angular upper limb kinematics (Zhou & Hu, 2007), simple pendulum motion (Brodie, Walmsley, & Page, 2008) and whole-body translational displacement involving acceleration and deceleration periods (Damgrave & Lutters, 2009). Damgrave and Lutters (2009) have suggested that changes in segment acceleration/deceleration, such as long-lasting postures (e.g. standing still) and high-speed movements (e.g. jumping), might compromise the accuracy of the IMC estimation. However, these authors did not provide any technical explanation for the reduced accuracy. However, Zhou et al. (2007) attributed the larger error of their IMC measurement to overshoots of the inertial sensors during periods of fast orientation change, which might have happened during the transition periods recorded in our study. Moreover, the reduced accuracy of IMC during changes in direction may be related to the ability of the sensors and fusion algorithm to detect and use gravity to produce accurate orientation estimations (Godwin et al., 2009). Our results corroborate these findings, as the accuracy during steady walking was greater than the accuracy from transition periods.

Ultimately, these limitations resulted in overestimation of the walking speed in these transition periods. Previous studies have highlighted the potential limitations of using the Kalman filter to establish segment orientation, as it focuses on the prediction of orientation from motion with a known Gaussian-error distribution (Brodie et al., 2008; Zhou & Hu, 2007). This fact may pose a limitation for this tool to accurately describe complex motion patterns involving changes in direction and stationary periods. Therefore, our results provide relevant information for system developers to further enhance the extraction of position and velocities from inertial sensors.

Despite the fact that IMCs can present limitations to accurately describe human kinematics, it is also important to highlight that OMC require appropriate processing to provide relevant results. Firstly, defining an appropriate calibration area is essential to maximise marker tracking and minimising errors. Our study was conducted in a large laboratory and the 3 x 2 m walking path was defined as the maximum area that could provide accurate trunk marker tracking (i.e., no missing markers) in the calibrated laboratory space. Secondly, the derivation of the trunk centre of mass speed from marker displacement data might amplify high-frequency noise present in the displacement data. This technical problem was minimised by the careful checking of the quality of all markers displacement offline for inconsistencies and data clipping. In addition, the low-pass filtering of the displacement data is another essential step to minimise the influence of high-frequency noise on the reported OMC trunk speed. Regarding inertial sensors, IMC systems require specific conditions for optimal performance, such as location of the experiment and gravitational attraction. Assuring that the location is free of magnetic interferences can improve the determination of the global reference frame, which subsequently allows for better accuracy of data extracted from the fusion algorithm (Lebel, Boissy, Hamel, & Duval, 2013). The increasing use of IMCs can expand the possibilities to perform human motion analysis, but more research is needed to deeply understand the limitations of such devices (Cutti, Giovanardi, Rocchi, & Davalli, 2006).

CONCLUSION

In summary, this study showed that the resultant trunk speed measured using an IMC is similar to the speed measured from a gold standard OMC in a standard walking task. However, the accuracy from IMCs to describe trunk speed was reduced during the transition phases that included short stationary periods. As a result, the trunk speed provided by the IMC during the transition phases was overestimated when compared to the OMC. It is likely that current limitations of the Kalman filter to correctly predict changes in directions have caused such reductions in accuracy. Inertial sensors currently represent an important advance to perform motion capture in real-world scenarios, but it is highly relevant to demonstrate its versatility and precision across all potential recording scenarios Therefore, future studies could apply different stationary periods, as well as different approaching/exit walking speed, to investigate the accuracy of IMC. This next step can contribute to the improvement of algorithms currently implemented in IMCs systems.

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Conflict of interest

The authors declare that they have no conflict of interest regarding this work

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Table 1. Total trunk displacement measured from the inertial (Dist-IMC) and the optical motion capture system (Dist-OMC) in the anterior-posterior (AP), medial lateral (ML) and vertical directions (VERT) during the 4-lap recordings in three different paths. The relative root mean square error (rRMSE) and agreement between measures of the two systems were computed for each path. The agreement is categorised as weak ($r \leq 0.35$), moderate ($0.35 < r \leq 0.67$), strong ($0.67 < r \leq 0.9$) and excellent ($r > 0.9$).

	1 x 1 m		**2 x 2 m**		**2 x 3 m**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Dist-IMC-AP (m)	10.648	2.145	30.521	2.975	50.510	6.043
Dist-OMC-AP (m)	11.136	2.424	30.705	2.479	50.093	5.429
rRMSE (%)	50.602	24.281	13.541	8.264	8.203	3.491
Agreement (*r*)	0.985	0.008	0.998	0.002	0.998	0.001
Dist-IMC-ML (m)	13.065	2.959	31.148	3.187	35.363	5.413
Dist-OMC-ML (m)	11.384	2.619	31.334	2.252	33.959	3.144
rRMSE (%)	26.285	15.295	13.995	3.965	17.345	8.376
Agreement (*r*)	0.985	0.023	0.995	0.004	0.996	0.003
Dist-IMC-VERT (m)	0.439	0.099	0.858	0.176	1.100	0.419
Dist-OMC-VERT (m)	0.439	0.123	0.669	0.180	0.811	0.181
rRMSE (%)	173.292	112.171	97.236	46.385	80.999	19.632
Agreement (*r*)	0.733	0.139	0.617	0.175	0.611	0.163

Table 2. Duration of walking laps and DEC/ACC periods, as well as the agreement and relative root mean square error (rRMSE) between IMC and OMC for each path. The agreement is categorised as weak ($r \leq 0.35$), moderate ($0.35 < r \leq 0.67$), strong ($0.67 < r \leq 0.9$) and excellent ($r > 0.9$).

	Trunk speed - walking			Trunk speed - DEC/ACC		
	Duration (s)	**Agreement (*r*)**	**rRMSE (%)**	**Duration (s)**	**Agreement (*r*)**	**rRMSE (%)**
1 x 1 m						
Mean	6.140	0.682	23.40	1.999	0.730	61.80
SD	1.142	0.174	7.89	0.518	0.098	14.20
2 x 2 m						
Mean	8.664	0.768	18.45	1.475	0.823	43.73
SD	0.627	0.158	6.54	0.538	0.062	9.14
2 x 3 m						
Mean	9.369	0.824	16.18	1.455	0.872	44.03
SD	0.747	0.134	7.37	0.477	0.049	13.49

Figure 1. Experimental design (A) in which human walking was recorded using an inertial (IMC) and an optical motion capture system (OMC). In B, resultant trunk speed extracted from the IMC (*dashed lines*) and the OMC (*solid lines*) throughout four laps on each of the three established paths (1 x 1, 2 x 2 and 2 x 3 m).

Figure 2. Location of the 17 inertial measurement units from the inertial motion capture (IMC) system (A). The IMC software automatically generated four spine segments (T8, T12, L3 and L5) based on the full- body recording. In B, location of the retro-reflexive markers used to track the trunk segment position.

Figure 3. Mean (SD) resultant trunk speed during walking (A) and in the DEC/ACC periods (B) for the three different paths. Data was recorded from an inertial motion capture system (IMC, *white bars*) and an optical motion tracking system (OMC, *black bars*). * denotes significant difference in relation to the 2 x 2 and 2 x 3 paths for both systems ($p<0.005$); † denotes significant difference in relation to the 2 x 3 path for both systems ($p<0.001$); ‡ denotes significant difference in relation to the OMC for all paths ($p<0.001$).