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24 Whole-body biomechanical load in running-based sports: the validity of

25 estimating ground reaction forces from segmental accelerations

26

27 Abstract

Objective: Unlike physiological loads, the biomechanical loads of training in running-based sports are still largely unexplored. This study, therefore, aimed to assess the validity of estimating ground reaction forces (GRF), as a measure of external whole-body biomechanical loading, from segmental accelerations.

Methods: Fifteen team-sport athletes performed accelerations, decelerations, 90° cuts and straight running at different speeds including sprinting. Full-body kinematics and GRF were recorded with a three-dimensional motion capture system and a single force platform respectively. GRF profiles were estimated as the sum of the product of all fifteen segmental masses and accelerations, or a reduced number of segments.

Results: Errors for GRF profiles estimated from fifteen segmental accelerations were low $(1-2 \text{ N} \cdot \text{kg}^{-1})$ for low-speed running, moderate (2-3 N·kg⁻¹) for accelerations, 90° cuts and moderate-speed running, but very high (>4 N·kg⁻¹) for decelerations and high-speed running. Similarly, impulse (2.3-11.1%), impact peak (9.2-28.5%) and loading rate (20.1-42.8%) errors varied across tasks. Moreover, mean errors increased from $3.26\pm1.72 \text{ N}\cdot\text{kg}^{-1}$ to $6.76\pm3.62 \text{ N}\cdot\text{kg}^{-1}$ across tasks when the number of segments was reduced.

43 Conclusions: Accuracy of estimated GRF profiles and loading characteristics was dependent on task, 44 and errors substantially increased when the number of segments was reduced. Using a direct 45 mechanical approach to estimate GRF from segmental accelerations is thus unlikely to be a valid 46 method to assess whole-body biomechanical loading across different dynamic and high-intensity 47 activities. Researchers and practitioners should, therefore, be very cautious when interpreting 48 accelerations from one or several segments, as these are unlikely to accurately represent external 49 whole-body biomechanical loads.

- 50 Keywords: Training load monitoring; Biomechanical loads; Full-body segmental accelerations;
- 51 Loading characteristics; Segment reductions

53 Introduction

54 Training loads are monitored in sports as part of a process which aims to enhance performance, whilst 55 simultaneously reducing the risk of injury. Although physiological loads have been investigated 56 extensively, biomechanical load measures are still limited and, therefore, largely unexplored ¹. Based 57 on the assumption that accelerations of the trunk are a good representation of whole-body centre of 58 mass (CoM) accelerations, trunk accelerometry derived load measures (e.g. New Body Load, Dynamic 59 Stress Load, PlayerLoad, Force Load) have been used to quantify and evaluate whole-body biomechanical loads ^{2–6}. However, evidence relating accelerations of the trunk to established measures 60 61 of biomechanical loading is yet lacking. In fact, it has been shown that accelerations of individual segments (including the trunk) cannot accurately represent whole-body biomechanical loads 7-11. 62 63 Ground reaction forces (GRFs) are a well-established measure of whole-body biomechanical loading. GRFs have been used to optimise sprint performance ^{12,13}, improve running economy ¹⁴ and identify or 64 reduce potential injury risk factors ^{15,16}, and might thus be used to further understand the role of 65 66 external biomechanical forces in performance enhancement and injury prevention. Moreover, GRF drives internal force production and contributes to internal stresses on e.g. muscles, tendons and bones 67 68 ^{17,18}, which are currently difficult to measure in the field ¹. Since these structure- or tissue-specific loads are the primary cause of e.g. overuse injuries ¹⁹, monitoring GRF in the field would be a first 69 70 step towards investigating internal biomechanical loads in more detail. However, valid methods for 71 accurately estimating GRF outside laboratory settings are currently unavailable.

72 Body-worn sensors, such as accelerometers, are commonly used in sports to measure and monitor numerous training load related metrics ^{20,21}. Given their widespread application to measure 73 accelerations of various body segments ^{22,23}, accelerometers might be used to estimate GRF, which can 74 75 be defined as the sum of the product of segmental mass and CoM accelerations of all body segments. 76 This alternative expression of Newton's second law provides a way by which the contribution of 77 multiple segmental accelerations to the GRF can be systematically examined, especially since 78 accelerations of the trunk or other individual segments have been shown to not be sufficient to 79 estimate GRF for several straight running and cutting activities 7-9,11,24. Other studies have indeed

shown that for constant speed running, GRF can be estimated from seven ²⁵ or eleven ²⁶ segmental
accelerations measured with a laboratory based motion capture system. However, it is unknown
whether GRF for dynamic and high-intensity activities frequently undertaken in running-based sports
(e.g. rapidly accelerating, decelerating, cutting, sprinting) can be accurately estimated from segmental
accelerations and/or what the minimal required number of segments is.

If simultaneously measured segmental accelerations can be used to estimate GRF, this might eventually allow GRF to be estimated in field settings and provide a meaningful measure of external whole-body biomechanical loading. The aim of this study was, therefore, 1) to investigate whether segmental accelerations measured in a laboratory setting can be used to estimate GRF for a variety of dynamic and high-intensity tasks typically performed during running-based (team-) sports, and 2) to determine the minimal number of segments required.

91 Methods

Participants. Fifteen team-sports athletes participated in this study (12 males and 3 females,
age 23±4 yrs, height 178±9 cm, body mass 73±10 kg). All participants were healthy and physically
active for at least three hours per week (sports participation 7±5 hrs per wk). This study was approved
by the Liverpool John Moores University ethics committee and participants provided informed
consent according to the ethics regulations.

97 Protocol. After a standardised warm-up, participants performed a range of dynamic and high-98 intensity running tasks including accelerations, decelerations, cutting, and steady running at constant 99 speeds ranging from 2 m \cdot s⁻¹ to maximal sprinting (~7 m \cdot s⁻¹, individual specific). Participants were 100 instructed to land with one whole foot on a single force platform embedded in the ground and 101 performed a minimum of five trials for each leg per task. For acceleration trials, participants were 102 instructed to accelerate from stand-still to their maximal sprinting speed (achieved in ~ 20 m), while 103 landing on the force platform for their second or third step of accelerating. For decelerations, 104 participants were instructed to decelerate as quickly as possible from maximal sprinting to immediate 105 stand-still, while landing on the force platform for their first or second step of decelerating. Cutting trials were performed as a sharp change of direction on the force platform at a 90° angle from the 106

straight running direction. Steady (straight) running trials were performed at a constant low (2-3 m·s⁻¹), moderate (4-5 m·s⁻¹) or high running speed (>6 m·s⁻¹), including maximal sprinting. Running speeds were measured with photocell timing gates (Brower Timing Systems, Draper, UT, USA) and controlled by giving verbal feedback to speed up or slow down after each trial. Only trials within a \pm 5% range of the target speed were included.

112 Kinematic and kinetic data collection. During the trials, full-body kinematic data were 113 collected using a seventy-six retro-reflective marker set attached to anatomical landmarks of the body 114 (appendix A). Three-dimensional kinematic and kinetic data were synchronously recorded with ten 115 infrared cameras (Qqus 300+, Qualisys Inc., Gothenburg, Sweden) sampling at 250 Hz, in 116 combination with a single force platform (9287B, 90x60 cm, Kistler Holding AG, Winterthur, 117 Switzerland) embedded in the ground, sampling at 3000 Hz. Marker positions and ground reaction 118 forces (GRF) were recorded, synchronised and tracked using Qualisys Track Manager Software (QTM 119 version 2.16, Qualisys Inc., Gothenberg, Sweden). A static calibration was recorded at the start of each 120 session to determine the local coordinate systems, joint centres and segment dimensions for each 121 participant. From the marker data, a fifteen segment (head, trunk, pelvis, upper arms, forearms, hands, 122 thighs, shanks and feet) six-degree-of-freedom model was built, with segment mass and inertial properties based on Dempster's regression equations ²⁷ and represented as geometric volumes ²⁸. 123 124 Kinematic and kinetic data were exported to Visual3D (C-motion, Germantown, MD, USA) and 125 Matlab (version R2017b, The MathWorks, Inc., Natick, MA, USA) for further processing and analysis. 126

127 Data processing and analysis. Marker trajectories and force platform data were filtered with a 128 2^{nd} order Butterworth low-pass filter with 20 Hz and 50 Hz cut-off frequencies respectively. Trunk 129 defining marker trajectories were, however, filtered at 10 Hz based on a sensitivity analysis for 130 optimal GRF prediction (appendix B). For each trial, touch-down and take-off from the force platform 131 were identified by a 20 N threshold of the vertical GRF and resultant GRF was calculated from the 132 three individual force components (F_x, F_y, F_z). The centre of mass (CoM) position for each segment 133 was used to define segmental movements from which accelerations were calculated as the double

- 134 differentiation (using three-point derivatives) of CoM motion along the three axes of the lab (x-y-z).
- 135 Resultant GRF curves were then estimated as the sum of the product of each segmental mass and CoM
- acceleration in the three directions, according to equation 1.

$$GRF_{res,estimated} = \sqrt{\left(\sum_{n=1}^{1,2,3,\dots,15} (a_{n,x} \cdot m_n)\right)^2 + \left(\sum_{n=1}^{1,2,3,\dots,15} (a_{n,y} \cdot m_n)\right)^2 + \left(\sum_{n=1}^{1,2,3,\dots,15} (a_{n,z} \cdot m_n)\right)^2}$$
Eq. 1

In which *a* is the segmental acceleration, *m* the segmental mass and *n* the number of segments
included. To determine the number of segments required to accurately estimate resultant GRF, all
different segment combinations to estimate GRF from were examined. A total of 32,676 unique
combinations were analysed with a minimum of one and a maximum of fifteen segments. To ensure a
constant total body mass, masses of the segments not included in a specific combination were equally
divided and added to the segmental masses that were part of that combination.

143 Measured and estimated GRF curves were normalised to each participant's body mass. Accuracy of 144 estimated GRF profiles was evaluated by the absolute and relative curve root mean square errors 145 (RMSE). In addition, the accuracy of estimated GRF loading characteristics impulse (area under the 146 GRF curve), impact peak (force peak during the first 30% of stance) and loading rate (average GRF 147 gradient from touch-down to impact peak) was calculated and assessed. RMSE was rated as very low (<1 N·kg⁻¹), low (1-2 N·kg⁻¹), moderate (2-3 N·kg⁻¹), high (3-4 N·kg⁻¹) or very high (>4 N·kg⁻¹). 148 149 RMSE values were analysed for all possible combinations of segments per task, as well as all trials 150 combined, to determine the best combination (i.e. lowest mean RMSE across trials) for each number 151 of segments. Estimated GRF loading characteristics errors were rated as very low (<5%), low (5-152 10%), moderate (10-15%), high (15-20%) or very high (>20%), which was based on meaningful performance or injury related differences in GRF ^{12,13,15}. Moreover, linear regression analyses were 153 154 performed between GRF loading characteristics (impulse, impact peak, loading rate) derived from the 155 estimated and measured GRF profiles. Regressions were performed per task, as well as for all trials 156 combined to examine the generalisability of GRF estimations across tasks, and rated as very weak $(R^{2}=0.1)$, weak $(R^{2}=0.1-0.3)$, moderate $(R^{2}=0.3-0.5)$, strong $(R^{2}=0.5-0.7)$, very strong $(R^{2}=0.7-0.9)$ or 157 extremely strong (R²=0.9-1)²⁹. Furthermore, Bland-Altman analyses ³⁰ were performed across tasks to 158

explore mean differences and 95% limits of agreement between the estimated and measured GRFloading characteristics.

161 **Results**

162Full body segmental accelerations. Accuracy of estimated GRF profiles from fifteen163segmental accelerations (full-body) varied across tasks (figure 1; table 1). Overall curve errors164(RMSE) were low for running at low speeds (2-3 m·s⁻¹) and moderate for accelerations, 90° cuts and165moderate-speed (4-5 m·s⁻¹) running. However, mean RMSE was very high for decelerations and high-166speed running (>6 m·s⁻¹).

The accuracy of estimated GRF loading characteristics varied between metrics and was dependent on task (table 1). Impulses were accurately estimated with very low errors for 90° cuts and running at constant low and moderate speeds, low errors for accelerations, and moderate errors for decelerations and high-speed running. Similarly, impact peaks were estimated with low to moderate (9.2-15%) errors for all tasks, except accelerations, which had very high (28.5%) impact peak errors. Loading rate errors however, were very high (20.1-42.8%) across all tasks.

173 Correlations and agreement between measured and estimated GRF loading characteristics across all 174 tasks varied. Impulses had extremely strong correlations, with a small bias and 95% confidence 175 interval of the limits of agreement (-0.04 to 0.45 N·s·kg⁻¹) (figure C.1 A and D; table 1). Despite the 176 very strong correlation and small bias for impact peaks however, there was a large variation of the 177 differences with limits of agreement ranging from -12.6 to 8.4 N·kg⁻¹ (figure C.1 B and E). 178 Furthermore, measured and estimated loading rates had a strong correlation (R² = 0.68), but a large 179 bias and limits of agreement (-985 to 397 N·kg⁻¹·s⁻¹) (figure C.1 C and F).

180 Segment reductions. The best combinations of segments across all tasks for each given 181 number of segments are shown in table C.1. GRF estimated from a single segment was the best across 182 tasks from trunk accelerations, despite mean RMSE being very high. Furthermore, the trunk was part 183 of all combinations of segments, and thus the main contributor to GRF, followed by the thighs, head, 184 shanks, arms, pelvis and feet (in descending order of importance).

Reducing the number of segmental accelerations to estimate GRF substantially increased errors for all tasks (figure 2). To achieve estimated GRF errors that were moderate or better ($<3 \text{ N}\cdot\text{kg}^{-1}$) for at least 50% of the combinations and trials, a minimum of two and three segments was required for low- and moderate-speed running respectively, but eight (90° cuts) and eleven (accelerations) for more dynamic tasks. Moreover, for the high-intensity tasks (decelerations and high-speed running) the majority of trials and combinations resulted in very high errors, regardless of the number of segment used (figure 2).

192 **Discussion**

193 Estimating GRF from full-body segmental accelerations. The main aim of this study was to 194 assess the validity of estimating ground reaction forces (GRF) from segmental accelerations for a 195 range of dynamic and high-intensity running tasks typically performed during running-based sports. 196 From all fifteen body segments, overall GRF profiles as well as specific loading characteristics were 197 estimated with varying accuracy. Overall loading errors (RMSE and impulse) for example, were 198 considerably lower for running at low and moderate speeds ($\sim 2-5\%$) compared to the higher intensity 199 tasks (e.g. decelerations, high-speed running) (~6-12%). Similarly, impact peak and loading rate errors 200 ranged from $\sim 9\%$ for the lower intensity tasks to >40% for higher intensity tasks (figure C.1 E and F). 201 Meaningful performance or injury related differences in loading characteristics can, however, be as 202 small as \sim 3-10% ^{12,13,15}. Errors of the magnitude observed in this study could thus already rule out 203 certain applications of monitoring GRF estimated from full-body segmental accelerations. Using a 204 direct mechanical approach to estimate GRF from full-body segmental accelerations might, therefore, 205 not be a valid method to assess whole-body biomechanical loading for dynamic and high-intensity 206 activities. Consequently, future research should investigate if segmental accelerations might be used to 207 assess more specific measures of biomechanical loading (e.g. internal structural loads).

208 Estimated GRF results in this study are comparable to other laboratory-based studies aiming to predict

209 GRF from marker trajectory data using a mechanical approach. The impulse errors for low-speed

210 running (2.3%), impact peak errors for moderate-speed running (9.2%) and correlations between

estimated and measured impact peaks for low- to high-speed running ($R^2=0.77-0.96$) found in the

trajectory data for comparable constant speed running tasks ^{25,26,31}. However, this study extends 213 214 beyond other studies in that similar results were also achieved for a range of high-intensity and 215 dynamic running tasks frequently undertaken in running-based sports. Moreover, previous studies 216 failed to include the mediolateral and anteroposterior components of acceleration and GRF^{25,31}, utilised small sample sizes ^{25,26,31} and/or investigated running on a treadmill rather than overground 217 ^{26,31}, all of which limit their ability to translate their findings from the lab to an applied sport setting. 218 219 In most running-based sports, the dynamic and high-intensity movements examined in this study are regularly performed ^{32–34}. The musculoskeletal demands of these tasks are high ^{35–37} and thus comprise 220 221 a large amount of the total biomechanical loads experienced during training and competition. 222 Therefore, highly accurate estimates of GRF loading characteristics across different tasks (including 223 decelerations and running at high speeds) are essential to explore and understand the biomechanical 224 demands of training in greater detail. As discussed above however, the loading characteristics errors 225 observed in this study might already rule out several performance and injury related applications of 226 monitoring GRF. Future work could, therefore, investigate if the strong to extremely strong 227 correlations between estimated and measured GRF characteristics found in this study (figure C1; table 228 1) can be used to recalculate and improve the estimated loading characteristics, to quantify the 229 biomechanical stresses of training more accurately.

current study are similar to results reported in previous studies that aimed to predict GRF from marker

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230 Segment reductions. Full-body wireless accelerometry suits have been shown to be a reliable 231 and valid method for simultaneously measuring accelerations of all body segments (e.g. Xsens MVN ³⁸) and have been used to estimate GRF and moments during walking ³⁹. It is, however, likely to be 232 233 unpractical to use these systems for load monitoring during training and competition on a day-to-day 234 basis. Therefore, we examined the effects of reducing the number of segments and the minimal 235 number of segments required for acceptable GRF estimates. Although the lower intensity tasks (low-236 and moderate-speed running) were relatively robust against segment reductions, estimated GRF 237 profiles for the more sport-specific dynamic and high-intensity tasks substantially deteriorated (figure 238 2). When the number of segmental accelerations was reduced to six segments for instance (i.e.

239 excluding the head, arms and feet), errors substantially increased to very high for all tasks (figure 2; 240 table C.1). Previous studies have reported similar findings of considerably decreased accuracy in whole-body CoM estimates (and thus GRF) for constant speed running⁷, side cutting¹¹, and jumping, 241 kicking and throwing ⁴⁰, when the number of segments was only slightly reduced. Furthermore, the 242 243 very high errors observed in this study for GRF estimated from one segment (i.e. the trunk) are in line 244 with other studies which reported that individual segmental accelerations cannot be used to accurately estimate GRF for steady running at constant speeds ^{7,9} and side cutting ^{8,11}. These findings, together 245 246 with the present results suggest that estimating GRF from one or several segmental accelerations using 247 a mechanical approach is not a valid method to accurately predict GRF for dynamic and high-intensity 248 running tasks.

249 A crucial requirement for GRF to be used as a meaningful measure of biomechanical loading in the 250 field, is that GRF estimates are highly accurate across different tasks. Since errors of the magnitude 251 observed in this study might already rule out certain applications as discussed above, the increased 252 GRF errors for a reduced number of segments probably further eliminate several aspects that make 253 GRF a meaningful load measure. Consequently, the usefulness of less accurate GRF estimates from a 254 reduced number of segments (and individual segmental accelerations from e.g. the trunk especially) as 255 a measure of biomechanical loading, is questionable. Researchers and practitioners should, therefore, 256 be very cautious when interpreting one or several segmental accelerations (or derived load measures), 257 as these are unlikely to be a valid and meaningful measure of whole-body biomechanical loading.

258 Alternative methods to assess whole-body biomechanical loading in the field. Segmental 259 accelerations used to estimate GRF in this study were derived from marker trajectory data recorded 260 with a three-dimensional motion capture system. Similar to force platforms, such systems are not 261 typically available in the field and if they are, data collection is laborious and impractical for 262 immediate analysis on a daily basis. In contrast to force platform and marker-based motion capture 263 technologies however, body-worn accelerometers are commonly used in the field and thus relatively easily accessible ^{20,21}. Moreover, the use of in-field markerless motion capture systems are currently on 264 265 the rise as a non-invasive way of quantifying movement in different sports ^{41–43}. Future research

should, therefore, investigate if body-worn (or even implantable ⁴⁴) accelerometers or markerless
motion capture systems can provide accurate measures of full-body segmental CoM accelerations, to
eventually estimate GRF in field settings.

269 This study aimed to estimate GRF from segmental accelerations using a direct mechanical approach. Alternative methods have, however, emerged that use machine learning methods to predict GRF ^{45–48}. 270 271 For example, neural network approaches have been used successfully to predict GRF from marker trajectory data ^{46,48} or body-worn accelerometers ^{45,47} for a variety of running tasks. Despite the 272 273 promising results, there might be disadvantages of using these computational rather than mechanical 274 approaches to estimate GRF for load monitoring purposes. Computational methods could prevent one 275 from exploring the underlying physical mechanisms of the predicted variable (e.g. GRF, joint 276 moments) which may limit its use for e.g. explaining injury mechanisms or defining performance 277 enhancing criteria. Machine learning could thus offer a powerful alternative for our mechanistic 278 approach, but future research should examine the explanatory ability of these methods for underlying 279 physical mechanisms.

280 Methodological limitations. A limitation of the mechanical approach described in this study is 281 that estimated GRF errors are solely due to measurement and methodological inaccuracies. Segmental 282 masses and inertial properties for example, were based on standardised values relative to the total body mass ²⁷ and standardised geometric shapes ²⁸ respectively. Future work could, therefore, investigate 283 284 how the present results might be improved by using participant-specific properties measured from e.g. a DXA scanner ^{49,50}. Other factors that could affect the estimated GRF accuracy are soft-tissue 285 artefacts ⁵¹ and filter cut-off frequencies ^{52,53}. For example, impact peak errors increased for higher 286 287 magnitudes, especially for decelerations (figure 2; table 1). These increased errors are likely due to the 288 considerably higher impacts, and consequent tissue vibrations, of landing for these higher-intensity 289 tasks. A sensitivity analysis of different cut-off filters showed that applying a lower 10 Hz filter to the 290 trunk marker (which typically were more affected due to their attachment to tight-fitting clothing 291 rather than the skin) resulted in the lowest estimated GRF errors across the different tasks (appendix 292 B). Future work should, however, consider the effects of soft-tissue artefact and filter cut-off

frequency, as well as the use of different filters for kinematic and kinetic data, when estimating GRFfrom segmental accelerations.

295 Conclusions

This study showed that accuracy of GRF profiles and loading characteristics estimated from full-body segmental accelerations is dependent on task. Moreover, errors substantially increased when the number of segments was reduced. It is, therefore, unlikely that one or several segmental accelerations can provide valid estimates of GRF for biomechanical load monitoring purposes, using a direct mechanical approach. Researchers and practitioners should, therefore, be very cautious when interpreting accelerations from one or several segments as these are unlikely to accurately represent external whole-body biomechanical loads.

303 Practical applications

- We suggest ground reaction forces (GRF) as a meaningful measure of overall whole-body
 biomechanical loading, and a first step towards investigating structure-specific internal loads,
 in running-based sports.
- Accuracy of GRF profiles and loading characteristics estimated from fifteen segmental
 accelerations was dependent on task, with higher accuracy for lower intensity tasks (e.g.
 running at low speeds). Moreover, errors substantially increased when the number of segments
 was reduced.
- A direct mechanical approach cannot provide valid estimates of GRF from segmental
 accelerations across dynamic and high-intensity running tasks that are frequently performed
 during running-based sports.
- Acceleration signals and derived training load measures from one or several segments are
 unlikely to accurately represent whole-body biomechanical loads.
- Researchers and practitioners should be very cautious when interpreting accelerations from
 one or several segments as a measure of external whole-body biomechanical loading.

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320 Supplementary files

- 321 Figure C.1 and table C.1 can be found in Appendix C. Appendices A, B and C are available as online
- 322 supplementary documents.

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Figure captions

Figure 1 Root mean square errors (RMSE) for resultant GRF curves estimated from fifteen segmental accelerations. Inset: representative measured (black solid line) and estimated (red dashed line) GRF profiles are shown, together with RMSE values for all acceleration (n=166), deceleration (n=161), 90° cut (n=171), low- (n=157), moderate- (n=157) and high-speed running (n=141) trials. Figure 2 Root mean square errors (RMSE) for estimated resultant GRF curves for each task. Bars represent the percentage of trials (primary y-axis) within the very low (<1 N·kg⁻¹), low (1-2 N·kg⁻¹), moderate (2-3 N·kg⁻¹), high (3-4 N·kg⁻¹) or very high (>4 N·kg⁻¹) error boundaries, and black dots represent the mean errors (secondary y-axis), for each given number of segments.







Table 1 Estimated resultant ground reaction force curve and loading characteristics errors											
	RMS	MSE Impulse error			Impact peak error			Loading rate error			
	$N \cdot kg^{-1}$	%	$N \cdot s \cdot kg^{-1}$	%	\mathbb{R}^2	N·kg ⁻¹	%	\mathbb{R}^2	$N \cdot kg^{-1} \cdot s^{-1}$	%	\mathbb{R}^2
Accelerations (n=166)	2.82 ±0.7	8.4 ±14	0.25 ±0.1	9.1 ±4	0.89	3.27 ±2.8	28.5 ±33	0.21	229 ±264	33.2 ±27	0.36
Decelerations (n=161)	5.77 ±1.8	$\begin{array}{c} 6.1 \\ \pm 8.8 \end{array}$	0.26 ±0.1	11.1 ±6	0.94	7.68 ±5.5	15 ±9	0.73	$\begin{array}{c} 380 \\ \pm 404 \end{array}$	$\begin{array}{c} 20.1 \\ \pm 16 \end{array}$	0.49
90° cuts (n=171)	2.67 ±0.7	3.3 ±4.1	0.21 ±0.1	3.8 ±2	0.98	3.33 ±2.9	9.8 ±8	0.75	234 ±210	24.5 ±18	0.60
Constant speed running											
Low (2-3 m·s ⁻¹ ; n=157)	1.62 ±0.4	1.8 ±2	$\begin{array}{c} 0.09 \\ \pm 0.06 \end{array}$	2.3 ±2	0.96	2.22 ±2.3	13.8 ±22	0.64	173 ±101	33 ±13	0.42
Moderate (4-5 m·s ⁻¹ ; n=157)	2.48 ±0.6	3.1 ±5.7	0.16 ±0.1	4.6 ±2	0.93	1.96 ±1.5	9.2 ±8	0.85	281 ±174	34 ±14	0.53
High (>6 m·s ⁻¹ ; n=141)	4.35 ±1.3	6.4 ±7.6	0.26 ±0.2	10.4 ±12	0.77	3.52 ±3.5	11.9 ±13	0.56	661 ±419	42.8 ±21	0.12
All tasks (n=953)	3.26 ±1.7	4.8 ±8.3	0.20 ±0.1	6.8 ±7	0.99	4.00 ±4.1	13.1 ±15	0.88	323 ±326	29.3 ±19	0.68

Root mean square error (RMSE), impulse, impact peak and loading rate errors of the resultant GRF estimated from fifteen segmental accelerations, for different tasks. Values are means \pm standard deviations and either absolute or relative errors compared to the measured resultant GRF. Regressions (R²) were performed per task as well as for all trials combined.

488 Appendix A: Marker attachment locations

489 Full-body kinematic data in this study were collected using a seventy-six retro-reflective marker set 490 attached to anatomical landmarks of the body. The aim of this appendix is to clarify the attachment 491 locations of segment defining and segment tracking markers (figure A.1). Markers for segment 492 definition (of which some were also used for segment tracking; see figure A.1) were attached to the 493 Calcaneus, lateral Calcaneus, first and fifth Metatarsus head, lateral/medial Malleolus, lateral/medial 494 Epicondyle of the Femur, Femur greater Trochanter, anterior/posterior Superior Iliac Spine, Iliac 495 Crest, Acromion, anterior/posterior head, shoulder, lateral/medial Epicondyle of the Humerus, Styloid 496 process of the Radius and Ulna, lateral/medial Metacarpal head (all left and right), Cervical vertebrae 497 7, Thoracic vertebrae 8, and the Jugular notch and Xiphoid process of the Sternum. In addition, marker 498 clusters for segment tracking were attached to the lateral sides of the shanks and thighs (four markers 499 per cluster), as well as the forearms and upper arms (three markers per cluster).



500 Figure A.1 Attachment locations of segment tracking markers (blue), segment defining markers (red) and

501

502

- 503

markers used for both (black).

504 Appendix B: Marker trajectory filter cut-off frequencies

505 *Objective*

Segmental accelerations used to estimate ground reaction forces (GRFs) in this study were derived from motion capture-based marker trajectories. Accuracy of estimated GRF profiles is thus dependent on marker trajectory processing before calculating the segmental centre of mass (CoM) accelerations. The aim of this appendix was, therefore, to investigate what filter cut-off frequency lead to the most accurate resultant GRF estimates.

511 *Methods*

512 Kinematic and kinetic data for ten subjects (7 males and 3 females, age 24±5 yrs, height 176±8 cm, 513 mass 72 ± 9 kg) was used (see the methods section of the main paper for more detail on the data collection and processing). Marker trajectories were filtered with a 2nd order Butterworth low-pass 514 515 filter using four different cut-off frequencies (25 Hz, 20 Hz, 15 Hz and 10 Hz), while force data were 516 filtered at 50 Hz. Visual screening of the data revealed relatively large trunk marker vibrations 517 compared to the other markers, which was likely due to marker attachment to the shirt rather than the 518 skin. Therefore, combinations of filter cut-off frequencies (20-15 Hz, 20-10 Hz and 15-10 Hz) were 519 also examined, i.e. markers defining the trunk segment were filtered at a lower cut-off frequency than 520 the other markers. Trunk defining markers that were filtered at a lower cut-off frequency were those 521 attached to the left and right Iliac Crest and Acromion, Cervical vertebrae 7, Thoracic vertebrae 8, and 522 the Jugular notch and Xiphoid process of the Sternum.

523 Results

524 Estimated GRF errors typically decreased for lower cut-off frequencies (table B.1). For higher

525 frequencies (25 Hz, 20 Hz) the estimated GRF profiles included more oscillations compared to the

526 lower cut-off frequencies (15 Hz, 10 Hz) (figure B.1). Consequently, RMSEs were lower across all

527 tasks when marker data were filtered at 15 Hz, compared to 25 and 20 Hz. However, only for

528 accelerations and constant speed running, errors were further reduced when a 10 Hz filter was applied,

- 529 while over-smoothing of estimated GRF profiles resulted in the loss of important GRF characteristics
- 530 (e.g. impact peak) for the other tasks (figure B.1 C, D, E). When a combination of two cut-off

frequencies (20-15, 20-10 and 15-10 Hz) was used, however, RMSE values were further reduced. For
most tasks separately, as well as all trials combined, a combination where the trunk was filtered at 10
Hz resulted in the most accurate GRF estimates (table B.1; figure B.1).



Figure B.1 Representative examples of measured resultant ground reaction force (GRF; black solid line) profiles
and resultant GRF estimated from marker trajectories filtered at 25 Hz (blue dotted line), 20-10 Hz (red dashed
line) or 10 Hz (green dashed line), for each task.

Table B.1 Marker trajectory filter cut-off frequency comparison								
	25 Hz	20 Hz	20-15 Hz	20-10 Hz	15 Hz	15-10 Hz	10 Hz	
Accelerations	3.7±1	3.4±0.9	3.1±0.8	2.8 ± 0.7	3±0.8	2.6±0.6	2.4±0.6	
Decelerations	7.7±2.4	7.4±2.3	6.8±2	6±1.8	7.3±2.2	6.4±1.9	8±2.5	
90° Cuts	$3.4{\pm}0.8$	$3.2{\pm}0.8$	3±0.7	2.7±0.7	3.1 ± 0.8	2.8 ± 0.7	3.4 ± 0.9	
Constant speed running								
Low (2-3 m·s ⁻¹)	2.3 ± 0.6	2.1 ± 0.6	$1.9{\pm}0.5$	1.7 ± 0.4	$1.9{\pm}0.5$	1.6±0.4	1.7 ± 0.5	
Moderate (4-5 m \cdot s ⁻¹)	3.3±0.9	3.1 ± 0.8	$2.9{\pm}0.7$	2.6±0.6	3±0.8	2.6±0.6	$2.9{\pm}0.7$	
High (>6 m·s ⁻¹)	5.4±1.3	5.1±1.3	4.8±1.2	4.4±1	4.9±1.2	4.4±1	4.7±1.3	
All tasks	4.3±2.2	4.1±2.1	3.8±2	3.4±1.7	$3.9{\pm}2.2$	3.4±1.9	3.9±2.5	

Root mean square errors (RMSE) for each (combination of) filter cut-off frequencies. Values are means \pm standard deviation per task, as well as all tasks combined. The best cut-off frequency per task is highlighted in green shading.

- 537 *Conclusions*
- 538 Estimated resultant GRF profiles were more accurate across tasks when a combination of different cut-
- 539 off frequencies was used for different markers. More specifically, the best results were obtained when
- 540 marker trajectories were filtered at a 20 Hz cut-off frequency, with trunk defining markers filtered at
- 541 10 Hz. These cut-off frequencies were, therefore, used to filter marker trajectory data before further
- 542 processing.



545 Figure C.1 Regression (A-C) and Bland-Altman (D-F) plots between measured and estimated



Table C.1 The best combinations of segments across all tasks for each given number of segments						
		RMSE (N·kg ⁻¹)				
#	Segments in the combination	Mean	SD			
1	Trunk	6.76	±3.62			
2	Trunk + thigh	5.91	± 3.17			
3	Trunk + thighs	4.54	± 2.48			
4	Trunk + thighs + pelvis	4.36	± 2.47			
5	Trunk + thighs + pelvis + head	4.00	± 1.94			
6	Trunk + thighs + pelvis + shanks	3.76	± 1.81			
7	Trunk + thighs + shanks + head + upper arm	3.61	± 1.66			
8	Trunk + thighs + shanks + head + upper arm + forearm	3.49	± 1.73			
9	Trunk + thighs + shanks + head + upper arms + forearm	3.42	± 1.75			
10	Trunk + thighs + shanks + head + upper arms + forearms	3.37	± 1.74			
11	Trunk + thighs + shanks + head + upper arms + forearms + hand	3.31	± 1.73			
12	Trunk + thighs + shanks + head + upper arms + forearms + hand + foot	3.28	± 1.72			
13	Trunk + thighs + shanks + head + upper arms + forearms + hand + feet	3.26	± 1.71			
14	Trunk + thighs + shanks + head + upper arms + forearms + hands + feet	3.26	± 1.71			
15	Trunk + thighs + shanks + head + upper arms + forearms + hands + feet + pelvis	3.26	±1.72			

Best combinations of segments (i.e. with the lowest mean root mean square errors (RMSE) across subjects, tasks and trials) for each number of segments. If only one of two segments was included in a combination (e.g. thigh or foot rather than thighs or feet), this was the segment on the side of the support leg. SD = standard deviation.