The feasibility of predicting ground reaction forces during running from a trunk accelerometry driven mass-spring-damper model

Niels J Nedergaard [1, 2], **Jasper Verheul** [1], **Barry Drust** [1], **Terence Etchells** [3], **Paulo Lisboa** [3], **Mark A Robinson** [1], **Jos Vanrenterghem** [Corresp. 1, 2]

[1] Research Institute for Sport and Exercise Sciences, Liverpool John Moores University, Liverpool, United Kingdom

[2] Department of Rehabilitation Sciences, Katholieke Universiteit Leuven, Leuven, Belgium

[3] School of Computing & Mathematical Sciences, Liverpool John Moores University, Liverpool, United Kingdom

Corresponding Author: Jos Vanrenterghem
Email address: jos.vanrenterghem@kuleuven.be

Background. Monitoring the external ground reaction forces (GRF) acting on the human body during running could help to understand how external loads influence tissue adaptation over time. Although mass-spring-damper (MSD) models have the potential to simulate the complex multi-segmental mechanics of the human body and predict GRF, these models currently require input from measured GRF limiting their application in field settings. Based on the hypothesis that the acceleration of the MSD-model's upper mass primarily represents the acceleration of the trunk segment, this paper explored the feasibility of using measured trunk accelerometry to estimate the MSD-model parameters required to predict GRF during running.

Methods. Twenty male athletes ran at approach speeds between 2 - 5 $m \cdot s^{-1}$. Resultant trunk accelerometry was used as a surrogate of the MSD-model upper mass acceleration to estimate the MSD-model parameters required to predict GRF. A purpose-built gradient descent optimisation routine was used where the MSD-model upper mass acceleration was fitted to the measured trunk accelerometer signal. Root mean squared errors (RMSE) were calculated to evaluate the accuracy of the trunk accelerometry fitting and GRF predictions. In addition, MSD-model parameters were estimated from fitting measured GRF, to explore the difference between model parameters estimated from trunk accelerometry and measured GRF.

Results. Despite a good match between the measured trunk accelerometry and the MSD-model's upper mass acceleration (median RMSE between 0.16 and 0.22 g), poor GRF predictions (median RMSE between 6.68 and 12.77 $N \cdot kg^{-1}$) were observed. In contrast, the MSD-model was able to replicate the measured GRF with high accuracy (median RMSE between 0.45 and 0.59 $N \cdot kg^{-1}$) across running speeds when model parameters were estimated from the measured GRF. The model parameters estimated from measured trunk accelerometry under- or overestimated the model parameters obtained from measured GRF, and generally demonstrated larger within parameter variations.

Discussion. Despite the potential of obtaining a close fit between the MSD-model's upper mass acceleration and the measured trunk accelerometry, the model parameters estimated from this process were inadequate to predict GRF waveforms during slow to moderate speed running. We therefore conclude that trunk-mounted accelerometry alone is inappropriate as input for the MSD-model to predict meaningful GRF waveforms. Further investigations are needed to continue to explore the feasibility of using body-worn micro sensor technology to drive simple human body models that would allow practitioners and researchers to estimate and monitor GRF waveforms in field settings.

The feasibility of predicting ground reaction forces during running from a trunk accelerometry driven mass-spring-damper model

Niels J Nedergaard[1,2], Jasper Verheul[1], Barry Drust[1], Terence Etchells[3], Paulo Lisboa[3], Mark A Robinson[1], Jos Vanrenterghem[1,2]

[1] Research Institute for Sport and Exercise Sciences, Liverpool John Moores University, Liverpool, United Kingdom

[2] Department of Rehabilitation Sciences, Katholieke Universiteit Leuven, Leuven, Belgium

[3] School of Computing & Mathematical Sciences, Liverpool John Moores University, Liverpool, United Kingdom

Corresponding Author:

Jos Vanrenterghem[1,2]

Tervuursevest 101 – box 1501, Leuven, 3001, Belgium

Email address: jos.vanrenterghem@kuleuven.be

Abstract

Background. Monitoring the external ground reaction forces (GRF) acting on the human body during running could help to understand how external loads influence tissue adaptation over time. Although mass-spring-damper (MSD) models have the potential to simulate the complex multi-segmental mechanics of the human body and predict GRF, these models currently require input from measured GRF limiting their application in field settings. Based on the hypothesis that the acceleration of the MSD-model's upper mass primarily represents the acceleration of the trunk segment, this paper explored the feasibility of using measured trunk accelerometry to estimate the MSD-model parameters required to predict GRF during running.

Methods. Twenty male athletes ran at approach speeds between 2 - 5 $m \cdot s^{-1}$. Resultant trunk accelerometry was used as a surrogate of the MSD-model upper mass acceleration to estimate the MSD-model parameters required to predict GRF. A purpose-built gradient descent optimisation routine was used where the MSD-model upper mass acceleration was fitted to the measured trunk accelerometer signal. Root mean squared errors (RMSE) were calculated to evaluate the accuracy of the trunk accelerometry fitting and GRF predictions. In addition, MSD-model parameters were estimated from fitting measured GRF, to explore the difference between model parameters estimated from trunk accelerometry and measured GRF.

Results. Despite a good match between the measured trunk accelerometry and the MSD-model's upper mass acceleration (median RMSE between 0.16 and 0.22 g), poor GRF predictions (median RMSE between 6.68 and 12.77 $N \cdot kg^{-1}$) were observed. In contrast, the MSD-model was able to replicate the measured GRF with high accuracy (median RMSE between 0.45 and 0.59 $N \cdot kg^{-1}$) across running speeds when model parameters were estimated from the

measured GRF. The model parameters estimated from measured trunk accelerometry under- or overestimated the model parameters obtained from measured GRF, and generally demonstrated larger within parameter variations.

Discussion. Despite the potential of obtaining a close fit between the MSD-model's upper mass acceleration and the measured trunk accelerometry, the model parameters estimated from this process were inadequate to predict GRF waveforms during slow to moderate speed running. We therefore conclude that trunk-mounted accelerometry alone is inappropriate as input for the MSD-model to predict meaningful GRF waveforms. Further investigations are needed to continue to explore the feasibility of using body-worn micro sensor technology to drive simple human body models that would allow practitioners and researchers to estimate and monitor GRF waveforms in field settings.

Introduction

Humans generate considerable forces against the ground during running to maintain an upright posture. This comes at the cost of equal and opposite ground reaction forces (GRF) acting on the body during every foot-ground contact (Cavanagh & Lafortune, 1980). These GRF put the body's soft tissues (e.g. bones, cartilage, muscles, tendons and ligaments) under biomechanical stresses which over time are expected to lead to beneficial structural adaptations (Kibler, Chandler & Stracener, 1992; Dye, 2005). Inadequate recovery or repetitive GRF with excessive magnitudes can instead lead to negative adaptions and tissue damage (Kibler, Chandler & Stracener, 1992; Dye, 2005). The ability to monitor an athlete's GRF during running can therefore help to better understand the relationship between the external forces experienced and soft-tissue adaptations (Vanrenterghem et al., 2017) ultimately helping to prevent musculoskeletal injury.

Monitoring GRF during running is currently restricted to laboratory environments where GRF are measured with force platforms built into the ground, or derived from whole-body kinematics (Bobbert, Schamhardt & Nigg, 1991; Winter, 2005). With recent developments of low-cost sensor based micro technology (Camomilla et al., 2018), accelerometry has become a popular tool to evaluate running mechanics outside laboratory environments in long and middle distance running (Tao et al., 2012) and professional team sports (Akenhead & Nassis, 2016). Accelerometry also offers opportunities to estimate GRF, and tibia-mounted accelerometry has for example been used as surrogate measure of peak GRF since the early 90s (Lafortune, 1991; Lafortune, Lake & Hennig, 1995). However, recent studies found weak to

moderate linear relationships between peak accelerations measured from body-worn accelerometry (trunk- and tibia-mounted accelerometers) and peak whole-body accelerations measured from force platforms during running (Wundersitz et al., 2013; Nedergaard et al., 2017; Raper et al., 2018). Since body-worn accelerometers only measure segmental acceleration, the use of a single accelerometer is inadequate to incorporate the complex multi-segmental accelerations that result in specific GRF patterns (Nedergaard et al., 2017). Recent studies have indicated that from the combination of three or more body-worn inertial sensors and machine learning one can estimate GRF and knee joint moments with reasonable accuracy during running related locomotion (Johnson et al., 2018; Wouda et al., 2018), but the broader application of such approaches is constrained by the requirement of multiple sensors, machine learning tools, and large data sets. Therefore, if it were possible to estimate accurate GRF waveforms from a single body-worn sensor, it would provide practitioners and researchers with a useful tool to monitor the biomechanical load in field settings.

Since the overall motion of the human body has a spring-like behaviour during running, simple mass-spring models, consisting of a single mass and spring, have been widely used to estimate the vertical GRF in field settings (e.g. Alexander, 1984; Blickhan, 1989; McMahon & Cheng, 1990). Moreover, such models have been used in combination with trunk-mounted accelerometry to estimate the required model parameters (Gaudino et al., 2013; Buchheit, Gray & Morin, 2015). Unfortunately, the initial high-frequency impact peak typically observed in the GRF waveform during running, which is speculated to be linked with negative tissue adaptations and risk of injury (Nigg, Cole & Bruggemann, 1995; Hreljac, Marshall & Hume, 2000;

Milner et al., 2006), cannot be estimated with this oversimplified model (Alexander, Bennett & Ker, 1986; Bullimore & Burn, 2007). A more complex mass-spring-damper model (MSD-model) better replicates the GRF waveforms for running, including both impact and active peaks (Derrick, Caldwell & Hamill, 2000). This model consists of a lower mass connected to a spring in parallel with a damper, representing the support leg during foot-ground contact, and an upper mass and spring representing the dynamics of the rest of the body. However, the ability to use trunk-mounted accelerometry to estimate the required model parameters for this model is yet unknown.

The aim of this study was to examine if the acceleration of the MSD-model's upper mass represents the acceleration of the trunk segment measured with trunk-mounted accelerometry during running. This hypothesis seems feasible, since the trunk segment represents half of the body mass (Dempster, 1955). If this provides a reasonable approximation, it might be feasible to estimate the required MSD-model parameters from trunk accelerometry to subsequently predict GRF from the MSD-model behaviour. Specifically, we therefore explored (1) the feasibility to estimate the MSD-model's eight natural model parameters from measured trunk accelerometry, and (2) whether these model parameters in fact predict reasonably accurate GRF waveforms during running at slow to moderate running speeds.

Materials & Methods

Subjects and protocol

Twenty healthy male athletes (age 22 ± 4 years, height 178 ± 8 cm, mass 76 ± 11 kg) who engaged in running related sports activities on a weekly basis volunteered to participate in this study. The institutional ethics committee at Liverpool John Moores University granted ethical approvalfor this study (ethics approval number: 09/SPS/010) in accordance with the Declaration of Helsinki, and written consent was obtained from all participants. After a warm-up and an individual number of familiarisation trials the participants were asked to run over a force platform at different running speeds of 2, 3, 4 and 5 $m \cdot s^{-1}$ (± 5%) in a randomised condition order. Running speeds were measured with photocell timing gates (Brower Timing System, Utah, USA) positioned 2 m apart and 2 m from the centre of the force platform as described in Vanrenterghem et al. (2012). The participants completed four trials of each running speed, landing on the force platform with their dominant leg.

Experimental measurements

Resultant ground reaction forces were measured (*GRF*) with a sampling frequency of 3000 Hz from a 0.9 x 0.6 m^2 Kistler force platform (9287C, Kistler Instruments Ltd., Winterthur, Switzerland). Resultant trunk accelerations (TrunkAcc) were simultaneously collected at 100 Hz using a tri-axial accelerometer (KXP94, Kionex, Inc., Ithaca, NY, USA) with an output range of ± 13 g embedded within a commercial GPS device (MinimaxX S4, Catapult Innovations, Scoresby, Australia) with a total weight of 67 grams and 88 x 50 x 19 mm in dimension. The GPS device was positioned on the dorsal part of the upper trunk between the scapulae within a small

pocket of a tight fitted elastic vest according to the manufacturer's recommendations (Boyd, Ball & Aughey, 2011). TrunkAcc and GRF were synchronised using a combination of time and event synchronisation as described in Nedergaard et al. (2017) and exported to Matlab (version R2016a, The MathWorks, Inc., Natick, MA, USA) where a 4th order recursive Butterworth low-pass filter with a cut-off frequency of 20 Hz was applied to GRF and TrunkAcc. Only data from the stance phase were collected, where touch down and take off were defined when the vertical GRF crossed a 20 N threshold.

Mass-spring-damper model

The complex multi-segmental dynamics of the human body during stance phase were modelled as a passive MSD-model (Alexander, Bennett & Ker, 1986; Derrick, Caldwell & Hamill, 2000). This model consists of two masses (Fig. 1); a lower point mass (m_2) on top of a linear spring (k_2) in parallel with a damper (c) representing the support leg; an upper point mass (m_1) representing the dynamics of the rest of the body and another linear spring (k_1) connecting the two masses.

The one-dimensional motion of the MSD-model was described by the acceleration of the two masses (Eqn. 5 and 6):

$$\lambda = \frac{m_1}{m_2} \quad (1)$$

$$\omega_1{}^2 = \frac{k_1}{m_1} = \frac{(1+\lambda)k_1}{\lambda M} \quad (2)$$

$$\omega_2{}^2 = \frac{k_2}{m_2} = \frac{(1+\lambda)k_2}{M} \quad (3)$$

$$\zeta = \frac{c}{2\sqrt{k_2 m_2}} \quad (4)$$

$$a_1 = -\omega_1{}^2(p_1 - p_2) + g \quad (5)$$

$$a_2 = -\omega_2{}^2 p_2 + \omega_1{}^2\lambda(p_1 - p_2) - 2\zeta\omega_2{}^2 v_2 + g \quad (6)$$

$$GRF_{model} = \frac{M\omega_2}{1+\lambda}(\omega_2 p_2 + 2\zeta v_2) \quad (7)$$

where p_1, p_2 v_1, v_2, a_1, and a_2 are the initial positions, velocities and, accelerations of the two masses (m_1 and m_2), respectively; λ is the mass ratio of the lower mass relative to the total body mass (Eqn. 1); $\omega_1{}^2$ and $\omega_2{}^2$ are the natural frequencies of the springs (Eqn. 2 and Eqn. 3) based on the linear spring constants (k_1 and k_2) and the mass of the two masses (m_1 and m_2); ζ is the damping ratio of the damper (Eqn. 4); and g is the acceleration from gravitational acceleration (-9.81 m·s^{-1}). The GRF acting on the MSD-model is calculated as in Eqn. 7, where M is the sum of the two masses (i.e. total body mass):

Model parameter estimation

To estimate the eight model parameters (p_1, p_2 v_1, v_2, $\omega_1{}^2$ $\omega_2{}^2$, ζ, λ), we used gravity corrected TrunkAcc from the stance phase as a surrogate of the MSD-model's upper mass acceleration (Fig. 2A). For each trial, model parameters were optimised by fitting the MSD-model's upper mass acceleration (a_1) to the TrunkAcc signal. A purpose-built gradient descent optimisation routine in Matlab was used, where the two second-order differential equations of the MSD-model's motion (Eqn. 5 and 6) were transformed to four first-order differential equations and solved numerically with a Runge Kutta 4th order method. Root mean squared error (RMSE)

between TrunkAcc and a_1 were calculated for every iteration to determine the optimal model parameter combination that best fitted TrunkAcc for the individual trials. The model parameters estimated from the TrunkAcc fitting were then used to predict the GRF from Eqn. 7. Furthermore, to help understand differences in estimated model parameters and the predicted versus measured GRF, we also estimated the eight model parameters by fitting the MSD-model to the measured GRF (Fig. 2B), similar to the approach previously described by Derrick et al. (2000).

Statistical analysis

Measured and modelled GRF were normalised to the participants' mass. RMSE between TrunkAcc and a_1, and between measured GRF and predicted GRF, were calculated to evaluate the accuracy of the TrunkAcc fitting and the predicted GRF, respectively. RMSE median and interquartile range (25^{th} to 75^{th} percentile) were calculated to determine the variation in the model's accuracy within and across running speeds. Similarly, the median and interquartile range (25^{th} to 75^{th} percentile) of the estimated model parameters were calculated to explore the variation within and across running speeds for the model parameters estimated both from measured TrunkAcc and GRF.

Results

The first step was to estimate the required model parameters that fit the MSD-model's upper mass acceleration to the measured TrunkAcc signal. The MSD-model was able to fit the measured TrunkAcc with good accuracy across running speeds, though a_1 systematically underestimated the magnitude of the first peak observed in the accelerometry signal (Fig. 3A). The median RMSE (interquartile range 25th to 75th percentile) of the TrunkAcc fitting increased from 0.16 (0.12; 0.22) g at the slowest running speed to between 0.21 (0.16; 0.26) g and 0.22 (0.16; 0.30) g for three faster running speeds. Though similar median RMSE values were observed across the three fastest running speeds, the interquartile range increased with increased running speeds (Fig. 3A). Despite the good match between a_1 and TrunkAcc, poor GRF predictions were observed across running speeds (Fig. 3B) and the median RMSE of the predicted GRF systematically increased with running speeds, from 6.68 (3.81; 15.30) N·kg^{-1} at 2 m·s^{-1} to 12.77 (7.78; 27.22) N·kg^{-1} at 5 m·s^{-1}.

Since the TrunkAcc estimated parameters resulted in poor GRF predictions, we next estimated the model parameters by fitting the MSD-model to the measured GRF waveforms (Fig. 2B) to determine if there was any difference between the two sets of model parameters and to compare the upper mass acceleration to the measured TrunkAcc. The MSD-model was able to replicate the measured GRF with high accuracy when model parameters were estimated to directly fit the measured GRF (Fig. 4B). This was reflected in the low RMSE median and interquartile ranges observed across all running speeds (2 m·s^{-1}: 0.45 (0.36; 0.60); 3 m·s^{-1}: 0.47 (0.37; 0.61); 4 m·s^{-1}: 0.53 (0.39; 0.66); 5 m·s^{-1}: 0.59 (0.46; 0.73); All Speeds: 0.51 (0.39; 0.64)

222 $N \cdot kg^{-1}$). However, the MSD-model's upper mass acceleration profiles then deviated
223 considerably from the acceleration profiles measured with trunk accelerometry (Fig. 4A). The
224 model parameters also differed considerably from those estimated from fitting measured
225 TrunkAcc (Fig. 4C and 4D). Namely, the model parameters demonstrated smaller within
226 parameter variation, which was especially evident for p_2 and v_2. Also, lower v_1 (median
227 difference 0.47 $m \cdot s^{-1}$) and higher v_2 (median difference -1.73 $m \cdot s^{-1}$) values were observed across
228 running speeds.
229

Discussion

This study illustrates that the MSD-model's upper mass acceleration could be fitted to the measured trunk accelerometry with high accuracy, but the model parameters estimated from this process did not lead to accurate predictions of GRF waveforms across a range of slow to moderate running speeds. Further analysis of the MSD-model behaviour when fitting to the measured GRF revealed a considerable discrepancy in model parameters compared to when fitting the MSD-model to measured trunk accelerometry signals. These results demonstrate that our initial hypothesis that the MSD-model's upper mass acceleration primarily represents the acceleration of the trunk was false.

Model parameter estimation

The eight model parameters are fundamental to calculating the GRF acting on the MSD-model, and though fitting TrunkAcc was successful, the model parameters estimated from this approach resulted in poor GRF predictions. Based on the equation of the upper mass acceleration (Eqn. 5) and the model parameters estimated from TrunkAcc, it seems that the MSD-model was able to fit the TrunkAcc by keeping the initial position of the upper mass (p_1) and lower mass (p_2) low, and by keeping the spring stiffness of the upper spring (ω_1^2) low. Whereas p_1 has minor influence on the predicted GRF, the velocity of the upper mass at initial contact (v_1) is indirectly influenced by changes in the initial upper mass position ($v_1 = \dot{p_1}$). Derrick et al. (2000) found that decreased v_1 has a large impact on the duration of the stance phase and therefore could have contributed to the overestimation of foot-ground contact (Fig. 3B). Similarly, the MSD-model decreased the spring stiffness of the upper spring (ω_1^2) to better

253 fit the two acceleration peaks typically observed in the TrunkAcc data, which has previously
254 been shown to increase the duration of the stance phase (Derrick, Caldwell & Hamill, 2000).
255 Furthermore, the MSD-model lowered the initial position of the lower mass (p_2), which
256 previously has been shown to both increase the GRF at touch down and decrease the
257 magnitude of the impact peak (Derrick, Caldwell & Hamill, 2000). We therefore believe that the
258 high GRF values observed in our GRF predictions at touch down (Fig. 3B) were primarily related
259 to the lower initial position of the lower mass (p_2) required to fit the upper mass acceleration to
260 the TrunkAcc. Finally, the MSD-model also kept the damping ratio (ζ) low to better fit the
261 magnitude of the two acceleration peaks in the TrunkAcc. Decreasing the damping ratio, has
262 however previously been shown to increase the oscillation in the model's GRF (Alexander,
263 Bennett & Ker, 1986; Derrick, Caldwell & Hamill, 2000), and may therefore explain why our GRF
264 predictions to a large extent include oscillating characteristics (Fig. 3B).
265
266 The comparison between model parameters estimated from the TrunkAcc and parameters
267 estimated from measured GRF, clearly demonstrates that the model is unsuitable for predicting
268 GRF from TrunkAcc. A closer look at the model parameters estimated from measured GRF,
269 showed that the median position and velocity of the lower mass (p_2 and v_2) was constant across
270 running speeds and only varied marginally within running speeds (Fig. 2C). In addition, only
271 small differences in median damping ratios (ζ) were observed between running speeds in this
272 study (ζ between 0.31 and 0.39 au). It was in fact kept constant (ζ = 0.35 au) in the study by
273 Derrick et al. (2000). Based on these observations we explored the effect of keeping p_2, v_2, and ζ
274 constant for all trials (using the median parameter estimated from fitting GRF across running

speeds), and for the remaining five model parameters use the trial specific parameters estimated from fitting a_1 to TrunkAcc to re-calculate the predicted GRF (Fig. S1). Whilst this decreased the variability of the GRF prediction (RMSE interquartile range) both within and across running speeds, only minor improvements were observed in the GRF prediction. This indicated that keeping selected model parameters constant would not substantially improve the GRF prediction in future studies. Furthermore, when selected model parameters were kept constant, the original interaction between the model parameters estimated from the TrunkAcc fitting was broken. In other words, such an approach is like solving a jigsaw with pieces from another jigsaw.

MSD-model hypothesis

If the trunk accelerometry data accurately represents the model's upper mass acceleration one would at least expect that the model parameters related to the motion and stiffness of the upper mass and spring (p_1, v_1, ω_1^2) would be close to the model parameters estimated when fitting measured GRF. This was however not the case, and therefore naturally raises the questions as to whether the upper mass acceleration is equivalent to the acceleration measured from trunk accelerometry during running. The trunk accelerometry driven MSD-model approach introduced in this study is based on the hypothesis that the model's upper mass primarily represents the mass and motion of the trunk segment (Alexander, Bennett & Ker, 1986; Derrick, Caldwell & Hamill, 2000). Our results suggest however that this is not the case, and that independent accelerations of other body segments (e.g. the swing leg and arms) significantly contribute to the MSD-model's upper mass accelerations. We therefore conclude

297 that the primary model hypothesis for this study was false, and that trunk-mounted
298 accelerometry alone is inappropriate as input for the MSD-model to predict meaningful GRF
299 waveforms.
300
301 A high initial peak related to the attenuation of the shock impact from the foot's collision with
302 the ground (Hamill, Derrick & Holt, 1995; Derrick, 2004) dominated the TrunkAcc signals across
303 running speeds. In contrast, a higher second peak related to the COM displacement during the
304 stance phase dominated the upper mass acceleration when the MSD-model was fitted to
305 measured GRF. This raised the technical question as to whether the poor GRF predictions
306 observed from the measured accelerometer signal were partly a consequence of an artificially
307 high frequency of that initial peak and whether the application of lower filter cut-off
308 frequencies (cut-off frequencies of 20 Hz in the present study) would improve GRF predictions.
309 To explore this, trunk accelerometry data of 10 representative participants was low-pass
310 filtered with cut-off frequencies of 15, 10 and 5 Hz (Fig. S2). Whilst low cut-off frequencies
311 (especially 10 and 5 Hz) to a large extent successfully removed the initial high-frequency peak in
312 the accelerometry signal, and the RMSE between TrunkAcc and upper mass acceleration
313 decreased, it only had a minor influence on the RMSE of the predicted GRF across running
314 speeds (Fig. S2). Therefore, accelerometry post-processing did not improve the GRF predictions
315 from TrunkAcc. This suggests that the trunk accelerometry signal in itself was not the main
316 reason for the poor GRF predictions, but rather an incorrect hypothesis that the MSD-model's
317 upper mass acceleration primarily represents the acceleration of the trunk segment.
318

Replicating GRF from measured GRF

Although TrunkAcc was unsuccessful in predicting GRF during running with a simple MSD-model, the MSD-model could successfully replicate measured GRF during slow to moderate running speeds. In fact, the inclusion of all eight model parameters in our optimisation routine, compared to only optimising the spring constants of the upper and lower spring (k_1 and k_2) and the position of the lower mass (p_2) (Derrick *et al.,* 2000) allowed us to replicate the measured GRF with higher accuracy. These findings illustrate that despite the MSD-model simplicity it has the ability to replicate and potentially predict GRF for a range of running speeds. Since the model parameters associated with the lower mass and spring are crucial to predict GRF (Eqn. 7), this may open opportunities to use segmental kinematics and/or accelerometry from lower extremities to estimate model parameters. Recent studies have for example shown promising results in predicting GRF during sprinting, in high level sprinters, when contact and flight time, in combination with kinematics from the ankle were used as input for a two-mass model (Udofa, Ryan & Weyand, 2016; Clark, Ryan & Weyand, 2017). Future studies is however still need to explore the use of body-worn micro sensor technology to drive simple human body models and predict GRF waveforms for a range running speeds.

Model limitations

A limitation with the MSD-model and the associated model parameters is that multiple parameter combinations exist when fitting the MSD-model to measured GRF waveforms. Whilst it could be of interest to further explore the physical meaning of the individual model parameters and their interactions, this was not possible due to the existence of multiple model

parameter solutions. Secondly, the MSD-model is a one-dimensional model, and therefore only allows the magnitude of the GRF to be estimated. We decided to predict the magnitude of the resultant GRF in our study, considering that we wanted to estimate the overall external biomechanical loading on the body, however we accept that others may prefer to predict the magnitude of the vertical GRF only. Ultimately, we believe that it is important to recognise that the MSD-model approach omits any direction specific load variations across running speeds, and that these may well be relevant in how the musculoskeletal tissues are exposed to stresses. Finally, the MSD-model is a passive elastic model and therefore does not account for additional energy generated by the body's "active" structures (muscles). Whilst a more complex model could account for this (Zadpoor & Nikooyan, 2010; Nikooyan & Zadpoor, 2011), it is questionable if this would allow for better GRF predictions from TrunkAcc. The complexity of such model would probably also defeat the overall purpose of using a simple model that is still applicable in field settings.

Conclusions

In this study, we demonstrated that the upper mass acceleration of a simple MSD-model can be fitted to measured trunk accelerometry signals with high accuracy during running at various speeds, but that the ensuing model parameters do not deliver accurate predictions of GRF waveforms. Despite the convenient hypothesis that the MSD-model's upper mass acceleration primarily represents the acceleration of the trunk, our results showed that this hypothesis is violated too much to still predict meaningful GRF waveforms. Nevertheless, further studies should continue to explore the use of data from wearable micro sensor technology to drive

363 simple human body models that could allow us to estimate GRF waveforms in field settings.
364 This would allow researchers and practitioners to better monitor the external biomechanical
365 loads to which the human body is exposed during running locomotion, ultimately supporting a
366 general quest towards field-based monitoring of tissue load-adaptation processes.
367

368 ## Acknowledgements

369 The authors would like to thank Ms Elena Eusterwiemann for her assistance with the data
370 collection.

372 **References**

373 Akenhead R., Nassis GP. 2016. Training Load and Player Monitoring in High-Level Football:
374 Current Practice and Perceptions. *International Journal of Sports Physiology and*
375 *Performance* 11:587–593. DOI: 10.1123/ijspp.2015-0331.
376 Alexander RM. 1984. Elastic Energy Stores in Running Vertebrates. *American Zoologist* 24:85–
377 94. DOI: 10.1093/icb/24.1.85.
378 Alexander RM., Bennett MB., Ker RF. 1986. Mechanical properties and function of the paw pads
379 of some mammals. *Journal of Zoology* 209:405–419. DOI: 10.1111/j.1469-
380 7998.1986.tb03601.x.
381 Blickhan R. 1989. The spring-mass model for running and hopping. *Journal of Biomechanics*
382 22:1217–1227. DOI: 10.1016/0021-9290(89)90224-8.
383 Bobbert MF., Schamhardt HC., Nigg BM. 1991. Calculation of vertical ground reaction force
384 estimates during running from positional data. *Journal of Biomechanics* 24:1095–1105.
385 DOI: 10.1016/0021-9290(91)90002-5.
386 Boyd LJ., Ball K., Aughey RJ. 2011. The Reliability of MinimaxX Accelerometers for Measuring
387 Physical Activity in Australian Football. *International Journal of Sports Physiology and*
388 *Performance* 6:311–321. DOI: 10.1123/ijspp.6.3.311.
389 Buchheit M., Gray AJ., Morin JB. 2015. Assessing Stride Variables and Vertical Stiffness with
390 GPS-Embedded Accelerometers: Preliminary Insights for the Monitoring of Neuromuscular
391 Fatigue on the Field. *Journal of Sports Science and Medicine* 14:698–701.
392 Bullimore SR., Burn JF. 2007. Ability of the planar spring-mass model to predict mechanical
393 parameters in running humans. *J Theor Biol* 248:686–695. DOI: 10.1016/j.jtbi.2007.06.004.

394 Camomilla V., Bergamini E., Fantozzi S., Vannozzi G. 2018. Trends Supporting the In-Field Use of
395 Wearable Inertial Sensors for Sport Performance Evaluation: A Systematic Review. *Sensors*
396 18:873. DOI: 10.3390/s18030873.
397 Cavanagh PR., Lafortune MA. 1980. Ground reaction forces in distance running. *Journal of*
398 *Biomechanics* 13:397–406. DOI: http://dx.doi.org/10.1016/0021-9290(80)90033-0.
399 Clark KP., Ryan LJ., Weyand PG. 2017. A general relationship links gait mechanics and running
400 ground reaction forces. *The Journal of Experimental Biology* 220:247–258. DOI:
401 10.1242/jeb.138057.
402 Dempster WT. 1955. Space requirements of the seated operator: geometrical, kinematic, and
403 mechanical aspects of the body with special reference to the limbs. Wright-Patterson Air
404 Force Base, Ohio: Wright Air Development Center.
405 Derrick TR. 2004. The effects of knee contact angle on impact forces and accelerations. *Med Sci*
406 *Sports Exerc* 36:832–837. DOI: 10.1249/01.MSS.0000126779.65353.CB.
407 Derrick TR., Caldwell GE., Hamill J. 2000. Modeling the stiffness characteristics of the human
408 body while running with various stride lengths. *Journal of Applied Biomechanics* 16:36–51.
409 DOI: 10.1123/jab.16.1.36.
410 Dye SF. 2005. The pathophysiology of patellofemoral pain: a tissue homeostasis perspective.
411 *Clin Orthop Relat Res* 436:100–110. DOI: 10.1097/01.blo.0000172303.74414.7d.
412 Gaudino P., Gaudino C., Alberti G., Minetti AE. 2013. Biomechanics and predicted energetics of
413 sprinting on sand: hints for soccer training. *J Sci Med Sport* 16:271–275. DOI:
414 10.1016/j.jsams.2012.07.003.
415 Hamill J., Derrick TR., Holt KG. 1995. Shock attenuation and stride frequency during running.

Human Movement Science 14:45–60. DOI: http://dx.doi.org/10.1016/0167-9457(95)00004-C.

Hreljac A., Marshall RN., Hume PA. 2000. Evaluation of lower extremity overuse injury potential in runners. *Med Sci Sports Exerc* 32:1635–1641.

Johnson WR., Mian A., Donnelly CJ., Lloyd D., Alderson J. 2018. Predicting athlete ground reaction forces and moments from motion capture. *Med Biol Eng Comput*. DOI: doi.org/10.1007/s11517-018-1802-7.

Kibler WB., Chandler TJ., Stracener ES. 1992. Musculoskeletal adaptations and injuries due to overtraining. *Exerc Sport Sci Rev* 20:99–126.

Lafortune MA. 1991. Three-dimensional acceleration of the tibia during walking and running. *Journal of Biomechanics* 24:877–886. DOI: 10.1016/0021-9290(91)90166-K.

Lafortune MA., Lake MJ., Hennig E. 1995. Transfer function between tibial acceleration and ground reaction force. *Journal of Biomechanics* 28:113–117. DOI: 10.1016/0021-9290(95)80014-X.

McMahon TA., Cheng GC. 1990. The mechanics of running: How does stiffness couple with speed? *Journal of Biomechanics* 23, Supple:65–78. DOI: http://dx.doi.org/10.1016/0021-9290(90)90042-2.

Milner CE., Ferber R., Pollard CD., Hamill J., Davis IS. 2006. Biomechanical factors associated with tibial stress fracture in female runners. *Med Sci Sports Exerc* 38:323–328. DOI: 10.1249/01.mss.0000183477.75808.92.

Nedergaard NJ., Robinson MA., Eusterwiemann E., Drust B., Lisboa PJ., Vanrenterghem J. 2017. The Relationship Between Whole-Body External Loading and Body-Worn Accelerometry

438 During Team-Sport Movements. *International Journal of Sports Physiology and*
439 *Performance* 12:18–26. DOI: 10.1123/ijspp.2015-0712.
440 Nigg BM., Cole GK., Bruggemann GP. 1995. Impact forces during heel-toe running. *Journal of*
441 *Applied Biomechanics* 11:407–432. DOI: 10.1123/jab.11.4.407.
442 Nikooyan AA., Zadpoor AA. 2011. An improved cost function for modeling of muscle activity
443 during running. *J Biomech* 44:984–987. DOI: 10.1016/j.jbiomech.2010.11.032.
444 Raper DP., Witchalls J., Philips EJ., Knight E., Drew MK., Waddington G. 2018. Use of a tibial
445 accelerometer to measure ground reaction force in running: A reliability and validity
446 comparison with force plates. *Journal of Science and Medicine in Sport* 21:84–88. DOI:
447 10.1016/j.jsams.2017.06.010.
448 Tao W., Liu T., Zheng R., Feng H. 2012. Gait analysis using wearable sensors. *Sensors* 12:2255–
449 2283. DOI: 10.3390/s120202255.
450 Udofa AB., Ryan LJ., Weyand PG. 2016. Impact forces during running: Loaded questions,
451 sensible outcomes. In: *2016 IEEE 13th International Conference on Wearable and*
452 *Implantable Body Sensor Networks (BSN)*. 371–376. DOI: 10.1109/BSN.2016.7516290.
453 Vanrenterghem J., Nedergaard NJ., Robinson MA., Drust B. 2017. Training Load Monitoring in
454 Team Sports: A Novel Framework Separating Physiological and Biomechanical Load-
455 Adaptation Pathways. *Sports medicine (Auckland, N.Z.)*. DOI: 10.1007/s40279-017-0714-2.
456 Vanrenterghem J., Venables E., Pataky T., Robinson MA. 2012. The effect of running speed on
457 knee mechanical loading in females during side cutting. *Journal of Biomechanics* 45:2444–
458 2449. DOI: 10.1016/j.jbiomech.2012.06.029.
459 Winter DA. 2005. *Biomechanics and motor control of human movement*. Hoboken, N.J.: John

Wiley & Sons. DOI: 10.1002/9780470549148.

Wouda FJ., Giuberti M., Bellusci G., Maartens E., Reenalda J., van Beijnum B-JF., Veltink PH. 2018. Estimation of Vertical Ground Reaction Forces and Sagittal Knee Kinematics During Running Using Three Inertial Sensors. *Frontiers in Physiology* 9:1–14. DOI: 10.3389/fphys.2018.00218.

Wundersitz DW., Netto KJ., Aisbett B., Gastin PB. 2013. Validity of an upper-body-mounted accelerometer to measure peak vertical and resultant force during running and change-of-direction tasks. *Sports Biomech* 12:403–412. DOI: 10.1080/14763141.2013.811284.

Zadpoor AA., Nikooyan AA. 2010. Modeling muscle activity to study the effects of footwear on the impact forces and vibrations of the human body during running. *Journal of Biomechanics* 43:186–193. DOI: 10.1016/j.jbiomech.2009.09.028.

Figure 1

An illustration of the human body represented as a MSD-model.

The MSD-model consists of a lower mass spring damper element (m_2, k_2, c) representing the support leg of the human body and an upper mass spring element (m_1, k_1) representing the rest of the human body.

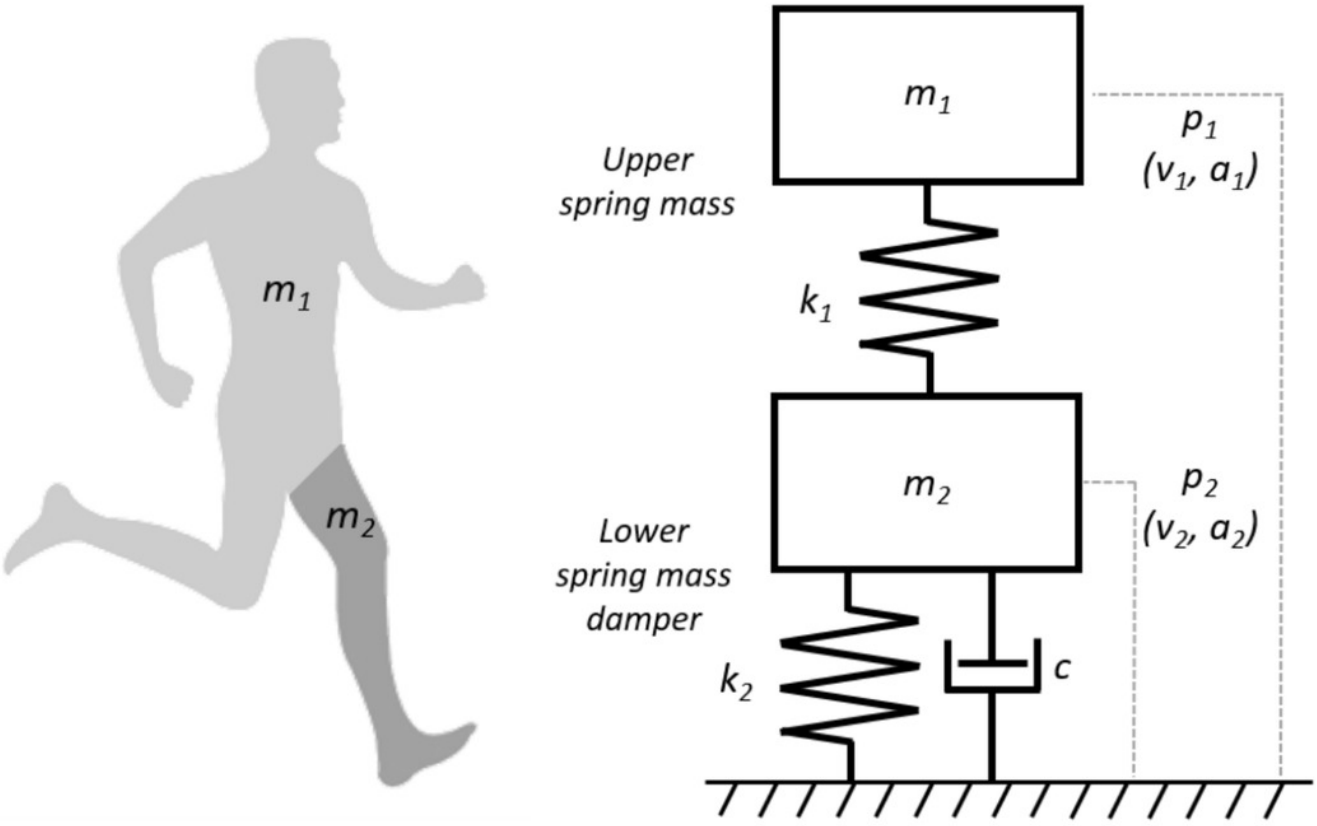


Figure 2

Estimating MSD-model parameters by fitting the MSD-model to measured trunk accelerometry and measured GRF.

The top panel (A) illustrates the trunk driven MSD-model where measured trunk accelerometry (TrunkAcc) for the stance phase, is used to estimate the eight model parameters, based on the hypothesis that the MSD-model's upper mass acceleration (a_1) primarily represents TrunkAcc, before GRF is calculated from the model parameter combination that best fitted TrunkAcc. The bottom panel (B) displays the traditional MSD-model approach, where the eight model parameters are estimated by fitting the model's GRF to the measured GRF.

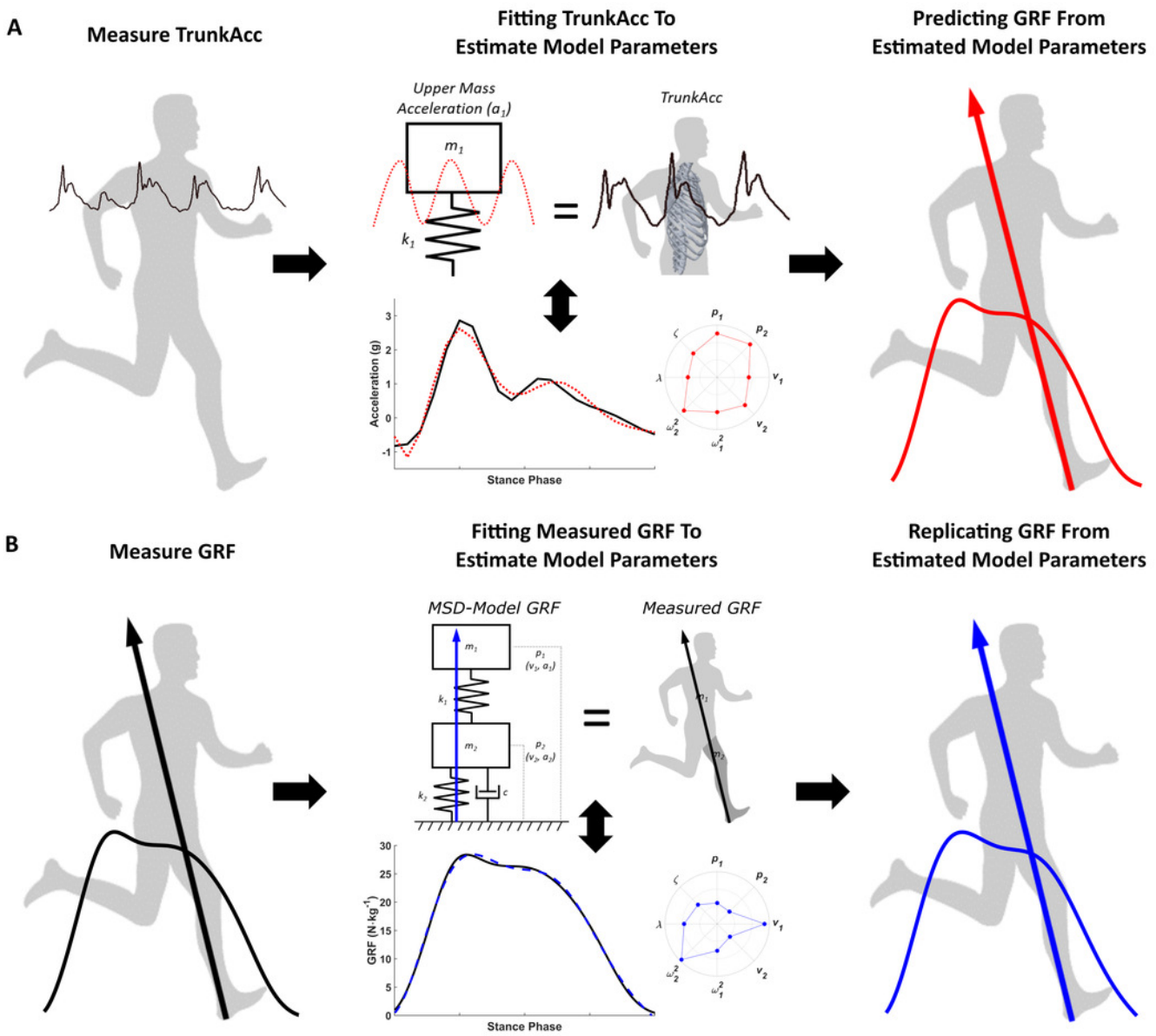

A
Measure TrunkAcc
Fitting TrunkAcc To
Estimate Model Parameters
Predicting GRF From
Estimated Model Parameters
Upper Mass
Acceleration (a_1)
TrunkAcc
m_1
k_1
Acceleration (g)
Stance Phase
B
Measure GRF
Fitting Measured GRF To
Estimate Model Parameters
Replicating GRF From
Estimated Model Parameters
MSD-Model GRF
Measured GRF
m_1
m_2
k_1
k_2
c
GRF (N·kg^{-1})
Stance Phase

Figure 3

Representative examples of the trunk accelerometry fitting and GRF prediction, and the median RMSE across running speeds.

Representative examples of fitting the upper mass acceleration to the trunk accelerometry signal across running speeds (A), and the measured and predicted GRF for the same trials (B). The RMSE for the trunk accelerometry fitting and GRF predictions are displayed in brackets for the individual examples. The boxplots on the right side display the RMSE median, and 25th and 75th interquartile range for the trunk accelerometry fitting and GRF prediction respectively across running speeds. Extreme outliers were removed from the boxplots.

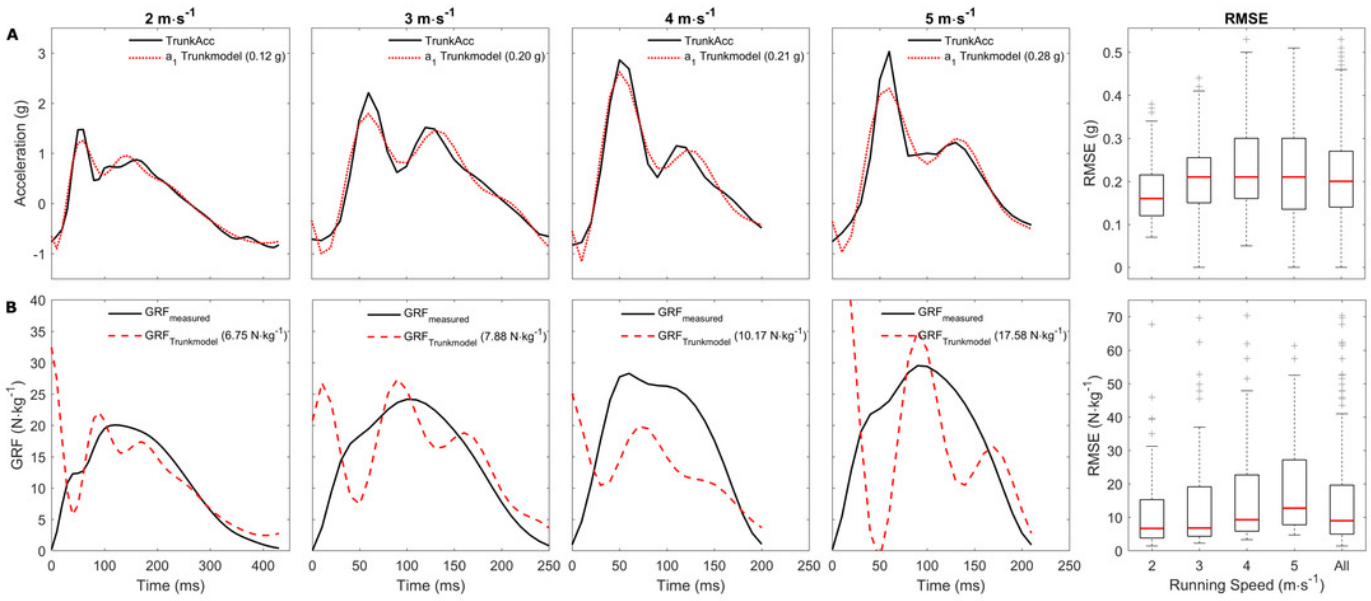
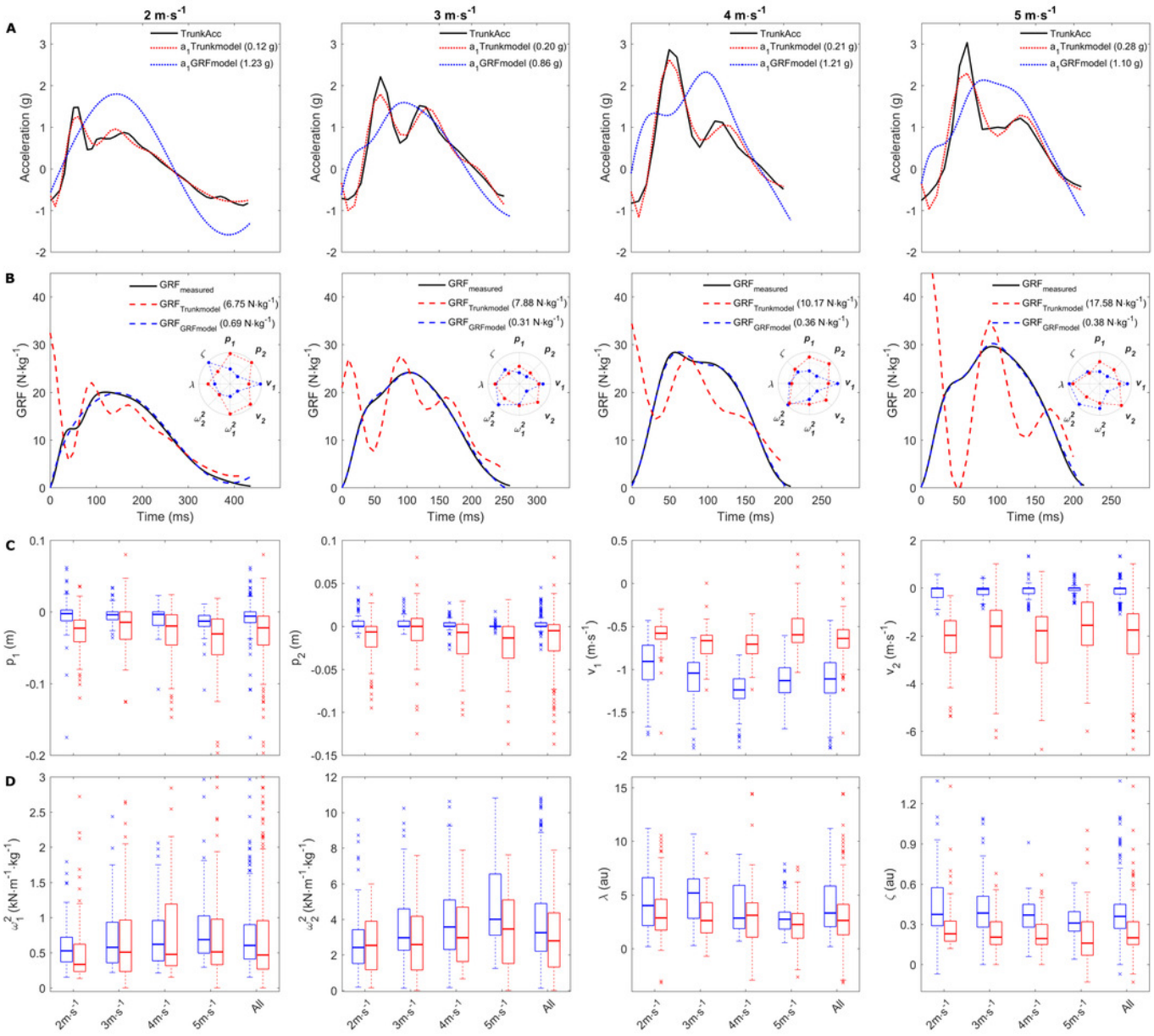


Figure 4

Representative examples of the upper mass acceleration, GRF and median model parameters from the TrunkAcc and GRF fitting.

Representative examples of the measured trunk accelerometry and the MSD-model's upper mass acceleration (A), and the measured, predicted and replicated GRF (B). The RMSE for the trunk accelerometry fitting and GRF predictions are displayed in the brackets for the individual examples. The inserted polar plots display the estimated model parameters (in unscaled values) from the two approached for the representative examples. The bottom two panels (C and D) display the median, 25^{th} and 75^{th} interquartile range for the model parameters estimated from measured trunk accelerometry and GRF respectively across running speeds. Extreme outliers were removed from the boxplots.


A
2 m·s-1
3 m·s-1
4 m·s-1
5 m·s-1
TrunkAcc
a1Trunkmodel (0.12 g)
a1GRFmodel (1.23 g)
a1Trunkmodel (0.20 g)
a1GRFmodel (0.86 g)
a1Trunkmodel (0.21 g)
a1GRFmodel (1.21 g)
a1Trunkmodel (0.28 g)
a1GRFmodel (1.10 g)
Acceleration (g)
B
GRFmeasured
GRFTrunkmodel (6.75 N·kg-1)
GRFGRFmodel (0.69 N·kg-1)
GRFTrunkmodel (7.88 N·kg-1)
GRFGRFmodel (0.31 N·kg-1)
GRFTrunkmodel (10.17 N·kg-1)
GRFGRFmodel (0.36 N·kg-1)
GRFTrunkmodel (17.58 N·kg-1)
GRFGRFmodel (0.38 N·kg-1)
GRF (N·kg-1)
Time (ms)
C
p1 (m)
p2 (m)
v1 (m·s-1)
v2 (m·s-1)
D
ω12 (kN·m-1·kg-1)
ω22 (kN·m-1·kg-1)
λ (au)
ζ (au)
2m·s-1
3m·s-1
4m·s-1
5m·s-1
All