

## COMPARING ESTIMATED AND MEASURED MUSCLE ACTIVATION DURING HIGHLY DYNAMIC AND MULTIDIRECTIONAL MOVEMENTS - A VALIDATION STUDY

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The purpose of this study was to validate muscle activation of the lower extremities computed in AnyBody<sup>MT</sup> with measured muscle activations (EMG) in highly dynamic movement tasks. Ten participants performed walking, jogging, sprinting and cutting tasks. Kinetic, kinematic and EMG data were captured for 8 muscles of the dominant leg. The average correlation coefficient (CC) was 0.51 (max.: 0.83, min.: -0.05) with 71% of all trials showing moderate to very good compliance. The average mean absolute error (MAE) was 1.32 (max.: 3.71, min.: 0.17). Co-contraction, precision of the muscle recruitment algorithm, electromechanical delay and anthropometrical measures may have affected the results. The estimation of computed muscle activation can be a suitable method for certain muscles considering highly dynamic movement tasks.

**KEY WORDS:** modelling, validation, AnyBody<sup>TM</sup>.

**INTRODUCTION:** The knowledge about muscle forces and activations, as well as joint forces and moments gives important insights into biomechanical aspects of statics and dynamics of the human body. This information is particularly relevant in the field of rehabilitation and athletic performance (Alexander & Schwameder, 2016). Direct measuring of the above mentioned parameters is often not applicable in the human body. Thus, a common method to analyse joint forces and moments is the inverse dynamic approach using musculoskeletal models. These models enable the calculation of muscle activation during fundamental activities like walking and more dynamic tasks including jogging, sprinting and cutting maneuvers.

However, the agreement between modelled and measured muscle activation using EMG remains still controversial, especially during highly dynamic activities. In this regard, several authors aimed to compare measured with predicted muscle activation, or muscle forces respectively. In a study by Wibawa, Verdonschot, Halbertsma, Burgerhof, Diercks & Verkerke, 2016 the authors reported a sufficient level of agreement between modelled and measured data during one-legged forward jumping and side jumping. Additionally, Alexander and Schwameder (2016) showed good agreement between both methods during ramp negotiations and hence considered the estimation of muscle activation using musculoskeletal models as applicable in biomechanical studies. Both studies used the standard model available in AnyBody<sup>TM</sup> Modelling System (MoCapModel, Anybody<sup>TM</sup> Technology, DK) which has a knee joint modelled as a hinge joint. In 2012, a further validated AnyBody<sup>TM</sup> model was presented at the "Grand challenge competition to predict in vivo knee loads". The validation comprised only level walking, whereas high dynamic tasks occurring in different types of sports were not considered.

Hence, the purpose of this study was to validate computed muscle activation during frequently performed dynamic movements using the slightly modified landmark scaled AnyBody<sup>TM</sup> model introduced by Andersen and Rasmussen (2011). The results aim to clarify to what extent the mentioned model is capable to predict sufficient valid muscle activation, aside from walking, during highly dynamic sports activities.

**METHODS:** Ten male participants performed five valid trials of each of the following testing conditions: walking (W), jogging (J), sprinting (S) and cutting (C). A trial was valid if the participants hit the force plate with the right, dominant foot. For W and J, the participants had to stay in a velocity range of 1.7m/s +/- 5% resp. 4.0m/s +/- 5%, which was controlled by the use of photoelectric sensors.

Motion analysis was performed using an optoelectronic 12-camera motion capture system (200 Hz, Vicon, Oxford, UK). Two force plates (1000 Hz, Kistler, CH) were embedded in the floor. Twenty-eight retro-reflective markers were attached to participants' feet, shanks, thighs and pelvis to create a nine-segment rigid body model. Participants' individual anthropometrics were measured to define the moments of inertia more accurately. The mass of a segment was assumed to be the product of the volume of a frustum and the segment's density. Kinematics and kinetics calculations were performed with AnyBody™ Modeling System using the anatomical landmark scaled model by Andersen and Rasmussen (2011). The knee joint was modeled as a spherical joint including three degrees of freedom, which were constrained using Anybody™'s Force-Dependent Kinematics method. A simple muscle model was used with third degree polynomial muscle recruitment. A 2nd-order Butterworth low pass filter (recursive, 20 Hz cut off) was applied for kinematic and kinetic data.

EMG was measured by means of a wireless system for 8 muscles (1000 Hz, myon, CH), following the SENIAM guidelines. Those muscles were the M. gluteus medius, M. gastrocnemius, M. soleus, M. biceps femoris, M. vastus medialis, M. tibialis anterior, M. semitendinosus and the M. vastus lateralis of the right, dominant leg. EMG signals were rectified and then smoothed using the root mean square method and a band pass filter (20 – 400 Hz) was applied. All EMG and modelled trials were normalized separately with respect to their maximum activation value during W. All trials were cut for force plate contact and subsequently normalized to 51 data points. Means for measured activation were calculated for each condition for each muscle. Trials above or under mean + 2 times standard deviation were excluded.

To compare the EMG and modelled activations, the correlation coefficient (CC) was computed for each muscle in each trial. Assumptions on the compliance were made according to the following categorization:  $CC < 0.2$  poor compliance,  $0.2 < CC < 0.4$  fair compliance,  $0.4 < CC < 0.6$  moderate compliance,  $0.6 < CC < 0.8$  good compliance,  $CC > 0.8$  very good compliance (Wibawa et al., 2016). Additionally, the mean absolute error (MAE) was calculated for each muscle and each trial as

$$MAE = \frac{\sum_{i=1}^n |MA_i - EMG_i|}{n}$$

$MA_i$  was the modelled activation and  $EMG_i$  was the measured activation. Data post-processing was conducted with Matlab 2016a (The MathWorks, Inc., US).

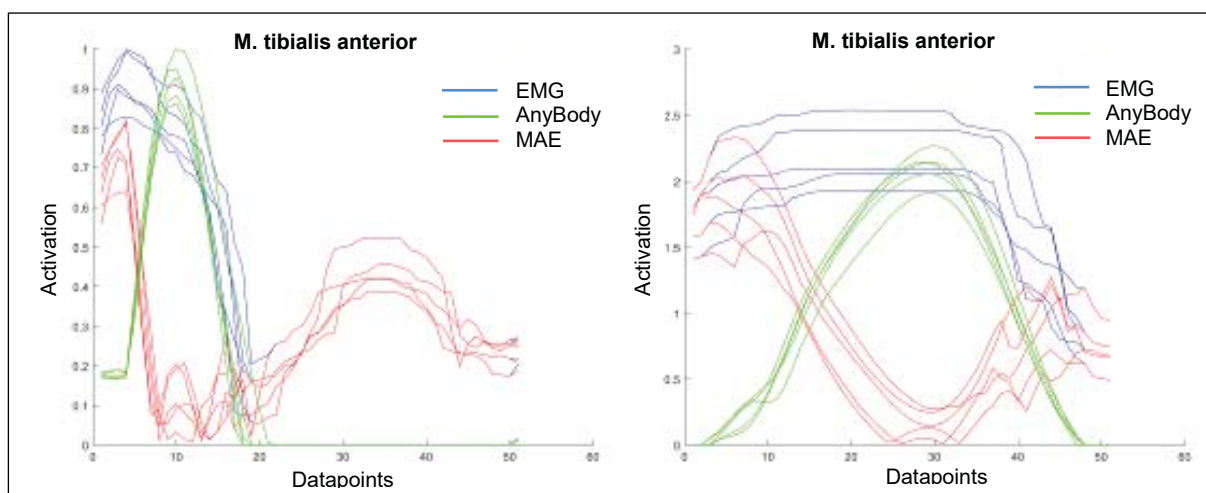
**RESULTS:** From overall 1600 data sets (10 participants, 4 conditions, 5 trials per condition, 8 muscles), 16 EMG data sets had to be excluded. The lowest activations were found in W and highest activations in S. This was consistent in measured and estimated activations. The average CC over all trials and muscles was 0.51. The maximum CC was 0.83 for the M. tibialis anterior in W and the minimum was -0.05 for the M. biceps femoris in C. 50% of the conditions and muscles showed good to very good compliance and 71% showed moderate to very good compliance. The average MAE amounted to 1.32 with a maximum of 3.71 for the M. vastus lateralis in S and a minimum for M. gastrocnemius medialis in W (0.17) (Table 1).

**Table 1**  
**Overview of the average (standard deviation) correlation coefficient and mean absolute error.**

	Correlation coefficient (CC)							
	Biceps femoris	Gastrocnemius med.	Gluteus medius	Semimembranosus	Soleus	Tibialis anterior	Vastus lateralis	Vastus medialis
Cutting	-0.05 (0.54)	0.53 (0.24)	0.42 (0.42)	0.39 (0.51)	0.72 (0.28)	0.33 (0.29)	0.76 (0.12)	0.74 (0.13)
Walking	0.41 (0.21)	0.82 (0.16)	-0.10 (0.23)	0.64 (0.23)	0.77 (0.32)	0.83 (0.06)	0.62 (0.11)	0.57 (0.15)
Jogging	-0.11 (0.50)	0.28 (0.24)	0.72 (0.07)	0.41 (0.43)	0.58 (0.11)	0.27 (0.40)	0.68 (0.06)	0.67 (0.15)
Sprinting	0.50 (0.30)	0.09 (0.26)	0.60 (0.28)	0.70 (0.30)	0.66 (0.16)	0.12 (0.33)	0.61 (0.12)	0.60 (0.11)
	Mean absolute error (MAE)							
	Biceps femoris	Gastrocnemius med	Gluteus medius	Semimembranosus	Soleus	Tibialis anterior	Vastus lateralis	Vastus medialis
Cutting	2.15 (0.91)	1.29 (0.78)	1.99 (1.44)	1.90 (0.64)	0.97 (0.45)	0.74 (0.30)	2.59 (1.35)	3.28 (3.19)
Walking	0.27 (0.04)	0.17 (0.04)	0.33 (0.06)	0.22 (0.07)	0.22 (0.06)	0.20 (0.06)	0.24 (0.08)	0.22 (0.05)
Jogging	1.33 (0.49)	0.94 (0.42)	0.62 (0.44)	1.09 (0.61)	0.77 (0.18)	0.46 (0.15)	1.03 (0.42)	1.47 (1.52)
Sprinting	3.04 (1.32)	1.13 (0.58)	2.69 (2.17)	2.54 (0.98)	1.02 (0.39)	0.89 (0.22)	2.28 (1.37)	3.71 (3.39)

The muscle with the highest average CC was M. soleus (0.68), followed by M. vasti (lat.: 0.66, med.: 0.64). M. biceps Femoris showed the lowest CC (0.26). The lowest MAE values were found for M. tibialis anterior (0.57) and M. soleus (0.74). The highest MAE value was exhibited by M. vastus medialis (2.17). Concerning the movement condition, W showed both the highest CC (0.59) and the lowest MAE (0.23), whereas S displayed a comparably high MAE (1.94) with only a moderate CC (0.48).

Figure 1 a) shows exemplarily the EMG activation, the estimated muscle activation and the associated absolute error of one participant for M. tibialis anterior during walking. MAE for this condition and this muscle were relatively small and CC comparably high.



**Figure 1:** Exemplary presentation of EMG, AnyBody™ signals and the corresponding mean absolute error of one participant. a) the M. tibialis anterior in walking and b) the M. soleus in jogging.

**DISCUSSION:** All 16 EMG data sets that had to be excluded from analysis were captured during C and S. The respective muscles were mainly the Mm. vasti and M. gastrocnemius. Both muscles and conditions are known to show high muscle oscillation in dynamic movements which leads to unnaturally high EMG activations (artefacts) or even electrode loosening. This is consistent with the results of the current study, since C and S were the conditions with the highest MAE and M. gastrocnemius as well as M. vastus medialis. Both exposed the greatest MAE values.

When comparing EMG and modelled muscle activation, it has to be kept in mind that AnyBody™ assumes a linear relation between muscle activity and muscle force. However it is known that this linearity does not exist. This might partly account for high MAE (Wibawa et al., 2016; Alexander & Schwameder, 2016). Since the measured and the modelled muscle activation are so different in nature, a mere statistical comparison might underestimate the rate of comparability. Thus, a visual inspection of the time series may be necessary (Wibawa et al., 2016). In the current study visual inspection and the CC suggest a relatively good model output, even if the MAE is relatively high. Visual inspection clarifies additionally that the modelled activations demonstrate a lot more hills and rises and drops to zero, which is consistent with the results described by Wibawa et al. (2016) and Erdemir, McLean, Herzog & van den Bogert, (2007). It displays a clear limitation of the model, because it only regards the muscle as active, as long as there is a change in joint angle.

The lack of implementation of co-contraction is one of several restrictions to the application of the model. The absence of antagonistic muscle activity can partly explain the limited level of agreement found with the CC and the MAE. Therefore, activities of muscles that do not contribute primarily to segment's motion are often underestimated by the model (Dubowsky et al., 2008; Pontonnier et al., 2014; Wibawa et al., 2016). This is true e.g. for the hamstring muscles in S and C in the second half of the movement. While EMG measurements still show a stabilizing activity of the leg flexors, the modelled activation declines heavily during

leg extension in S and C. In this regard, there are first attempts to address the co-contraction issue by including EMG-driven forward-dynamic estimation of muscle activation in OpenSim. Furthermore, the unnatural muscle recruitment of musculoskeletal models and the so called electro-mechanical delay compromise the level of agreement between the computed muscle activation and EMG signals. EMG activations could be time shifted ahead of the actual movement (approx. 30 to 100 ms) in order to account for the electromechanical delay that should reduce MAE values (Figure 1 a, b).

**CONCLUSION:** Modelling is a powerful tool to estimate muscle activation. Since direct validations are not feasible for highly dynamic and multidirectional movements, an indirect validation with EMG measurements is necessary. In this study, statistical parameters showed a moderate to good compliance for the majority of all data sets. MAE are assumed to be overestimated because of muscle oscillation and cross-talk, influencing EMG signals. A time shift of the EMG signal to account for electromechanical delay could further improve the statistical compliance. Additionally, a more individualized model with more sophisticated muscle recruitment algorithms and consideration of co-contraction by EMG data input could improve the outcomes. Conclusively, the applicability of the model following the indirect validation suggests that it can be used to estimate muscle activation, whereas further improvements can be made to achieve more valid results.

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