Computers in Biology and Medicine 175 (2024) 108524

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

AST: An OpenSim-based tool for the automatic scaling of generic musculoskeletal models

Andrea Di Pietro [a,*], Alex Bersani [b,c], Cristina Curreli [c], Francesca Di Puccio [a,d]

[a] Department of Civil and Industrial Engineering, University of Pisa, Italy
[b] Department of Industrial Engineering, Alma Mater Studiorum - University of Bologna, Italy
[c] Medical Technology Lab, IRCCS Istituto Ortopedico Rizzoli, Bologna, Italy
[d] Center for Rehabilitative Medicine "Sport and Anatomy", University of Pisa, Italy

ARTICLE INFO

Keywords:
Musculoskeletal models
OpenSim
Scaling tool
Automation
Marker placement
Matlab

ABSTRACT

Background and objectives: The paper introduces a tool called Automatic Scaling Tool (AST) designed for improving and expediting musculoskeletal (MSK) simulations based on generic models in OpenSim. Scaling is a crucial initial step in MSK analyses, involving the correction of virtual marker locations on a model to align with actual experimental markers.
Methods: The AST automates this process by iteratively adjusting virtual markers using scaling and inverse kinematics on a static trial. It evaluates the root mean square error (RMSE) and maximum marker error, implementing corrective actions until achieving the desired accuracy level. The tool determines whether to scale a segment with a marker-based or constant scaling factor based on checks on RMSE and segment scaling factors.
Results: Testing on three generic MSK models demonstrated that the AST significantly outperformed manual scaling by an expert operator. The RMSE for static trials was one order of magnitude lower, and for gait tasks, it was five times lower (8.5 ± 0.76 mm vs. 44.5 ± 7.5 mm). The AST consistently achieved the desired level of accuracy in less than 100 iterations, providing reliable scaled MSK models within a relatively brief timeframe, ranging from minutes to hours depending on model complexity.
Conclusions: The paper concludes that AST can greatly benefit the biomechanical community by quickly and accurately scaling generic models, a critical first step in MSK analyses. Further validation through additional experimental datasets and generic models is proposed for future tests.

1. Introduction

Musculoskeletal (MSK) models are considered powerful tools in the field of computational biomechanics to study human movement, neuromotor coordination, design-assisted devices and so on [1]. The reason behind the use of MSK models lies in their ability to provide information on quantities not directly accessible or measurable in vivo, such as joint reaction forces, muscle forces and muscle activations.

It is possible to distinguish two main types of MSK models: subject-specific models obtained by medical images (e.g., MRI and CT scans) of a specific patient and scaled generic models that are generated by scaling a generic predefined model (GM) to the anthropometric dimensions of a subject. The selection of the most suitable MSK model type, i.e. subject-specific vs. scaled GM, derives from a cost-benefit analysis, which aims to balance the trade-off between accuracy and speed of the analysis [2]. Subject-specific models are generally considered more accurate than scaled generic ones: they can represent musculo-tendon mechanics more precisely [3] and offer a more reliable assessment of joint axes definition [4]. However, generating a subject-specific model is much more time-consuming than scaling a GM to the size of a specific patient: it requires strong efforts on behalf of the operator to reproduce the subject geometry of bones and soft tissues along with incorporating their biomechanical characteristics by following well-established workflows [5].

The definition of a scaled GM is quicker but the scaling procedure is a critical step that needs to be carefully executed. It mainly consists of

Abbreviations: MSK, musculoskeletal; RMSE, root mean square error; GM, generic model; ASF, average scaling factor; SFR, scaling factor range; SSF, segment scaling factor; DoFs, degrees of freedom.

* Corresponding author. Department of Civil and Industrial Engineering, University of Pisa, Largo Lucio Lazzarino 1, Pisa, 56122, Italy.
E-mail addresses: andrea.dipietro@phd.unipi.it, andrea.dipietro94@gmail.com (A. Di Pietro).

https://doi.org/10.1016/j.compbiomed.2024.108524
Received 8 January 2024; Received in revised form 22 April 2024; Accepted 24 April 2024
Available online 26 April 2024

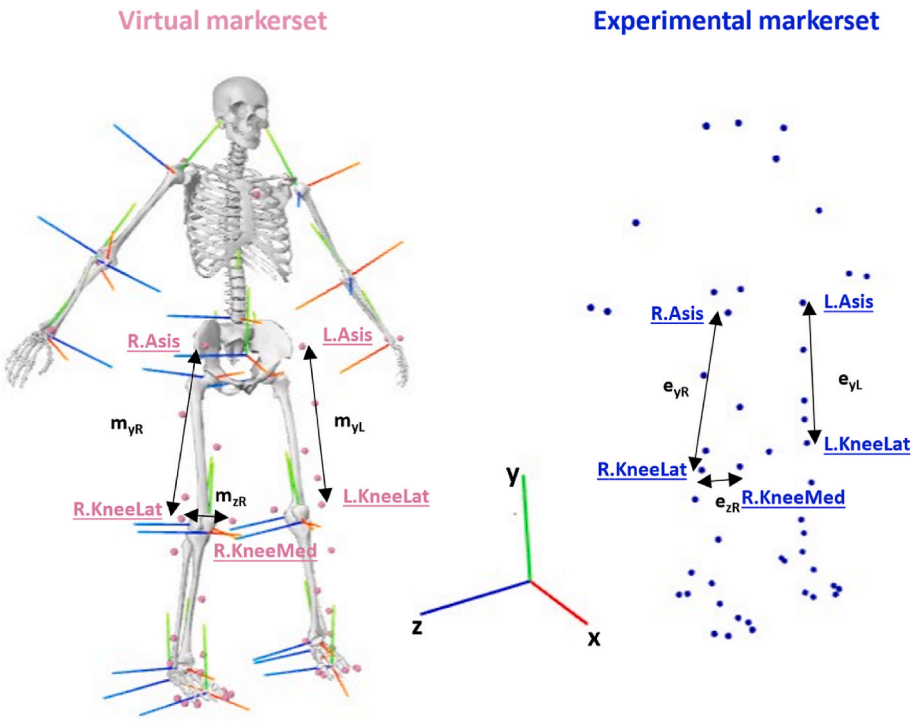

Fig. 1. Experimental (e_{yL}, e_{yR} *and* e_{zR}) and virtual (m_{yL}, m_{yR} *and* m_{zR}) marker distances used for scaling model femurs/thigh. Different scaling methodology (symmetrical/asymmetrical, isotropic/anisotropic) can be used for the scaling of model segments. Experimental markerset is defined in the laboratory coordinate system; each virtual marker, instead, is defined in a specific segment coordinate system.

modifying the selected GM's segment dimensions to represent the subject's anthropometric size under examination [6,7]. It is crucial since it is the first step of an MSK analysis and any error during this process can lead to inaccuracies for all the subsequent steps [7,8] and may compromise the validity and reliability of the model results [9,10].

The aim of this study is the development of an automatic tool for OpenSim to estimate the scale factors that best match experimental data: it is a challenging operation that requires moving virtual markers to match the actual position of the experimental ones [9]. Normally, it is manually executed through the GUI of OpenSim, in an iterative and time-consuming trial-and-error procedure. Guidelines provided by the developers of OpenSim [11] recommend to iterate the scaling procedure until the marker root mean square error (RMSE) is below 1 cm and the maximum error below 2 cm for markers referred to bony landmarks. Moreover, as asserted by Dunne et al. [7], markers adjusting is a highly user dependent operation, and even skilled users can make errors in estimating the effective 3D location of virtual markers.

Within the biomechanics field, over the years, the increasing availability of data has led to a growing demand for expediting the scaling process. Reinbolt and Charlton [12,13] are the first authors who automated this process, even before the OpenSim establishment, by employing bi-level optimization methods. This approach includes an outer optimization loop that fine-tunes scaling parameters and marker registrations based on the results of inverse kinematics obtained from the inner optimization loop. Besides the computational inefficiency noted in these methods [14], the Reinbolt one [12], in particular, proved to be sensitive to noisy experimental data, impacting the overall optimization process. Recently, a similar approach has been exploited by the developers of OpenSim by launching AddBiomechanics [14], a web application aiming at rapidly and automatically scale GMs using experimental data.

Pursuing similar aims but differing in the approach, this study does not employ optimization methods but tries to replicate the operations manually done by an OpenSim user to obtain a properly scaled model. To the best of our knowledge, such an approach has not yet been pursued.

2. Materials and methods

2.1. Marker-based scaling

Within the Motion Capture methodology, reflective experimental markers are commonly used to track the 3D motion of the investigated subjects. The placement of experimental markers on bony landmarks follows well-defined criteria [15–18] and protocols [19,20] which also account for the number of markers required to achieve the desired accuracy and, simultaneously, to minimize the time of the test [21]. Usually, a markerset includes both markers placed on bony landmarks, commonly used for subject calibration and scaling purposes, and markers (usually triads) positioned on the muscle belly of the limbs for motion tracking intents.

Virtual markers, conversely, are the "digital copy" of the experimental ones and are placed on the virtual reference skeleton of the GM by the operator (Fig. 1). One key issue of this step is that the operator should imagine and consider the thickness of soft tissues.

The OpenSim Scale tool employs a linear approach to resize the segment of the GM to the anthropometric measurements of the subject under investigation. Each segment of the GMs is resized by multiplying its original dimensions by a Segment Scaling Factor (SSF) determined as the ratio of the distances between experimental and virtual marker pairs (also known as measurement set).

For example, in Fig. 1, markers on the ASIS and the knee epicondyles are used to scale the thigh. The operator has to choose among several options:

a) Use different SSFs for the right and left and right thigh, TSF_R and TSF_L, e.g. if there is a known asymmetry in the patient:

$$TSF_R = \frac{e_{yR}}{m_{yR}} \text{ and } TSF_L = \frac{e_{yL}}{m_{yL}} \quad (1,2)$$

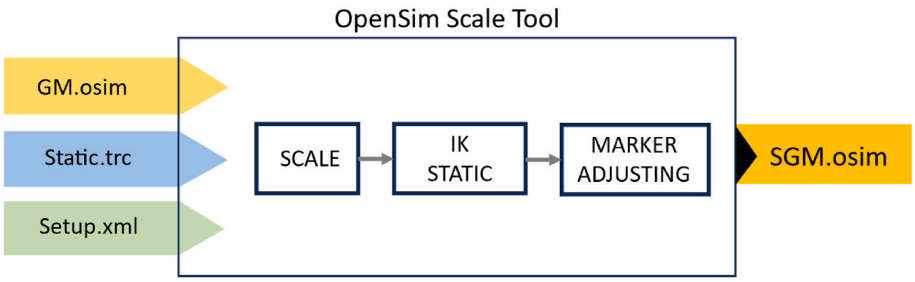

Fig. 2. Input of the tool: unscaled generic MSK model (GM.osim), static experimental pose (Static.trc) and scaling setup file defined by the user (Setup.xml). The output of the model is the scaled generic MSK model (SGM.osim). The phases of the OpenSim Scaling tool comprise: geometry scaling, inverse kinematics of the static pose and eventually, marker adjusting.

where e is the distance between experimental markers and m the distance between virtual ones (symbols are shown in Fig. 1).

b) An average SSF can be used for both sides:

$$TSF = \frac{1}{2}\left(\frac{e_{yR}}{m_{yR}} + \frac{e_{yL}}{m_{yL}}\right) \tag{3}$$

Similarly, more pairs of markers could be used to calculate an SSF.

c) Another option is to adopt a non-uniform scaling criterion, i.e. use different factors for the three dimensions which is also suggested as good practice in the OpenSim guide [11]. This can be important for example when the subject is tall and thin or short but plump. For example, two different scaling factors can be defined, considering Fig. 1, referring to both the y-direction (the long axis of the femur) and the x-z transverse directions:

$$\begin{aligned} TSF_y &= \frac{1}{2}\left(\frac{e_{yR}}{m_{yR}} + \frac{e_{yL}}{m_{yL}}\right) \text{ and} \\ TSF_x = TSF_z &= \frac{1}{2}\left(\frac{e_{zR}}{m_{zR}} + \frac{e_{zL}}{m_{zL}}\right) \end{aligned} \tag{4,5}$$

In this case, they were considered equal for the left and right sides but could also be different.

Summing up, the main causes of a "rough" marker-based scaling are due to a combination of two types of marker misplacements:

a) Virtual marker: they are located on the generic virtual model trying to consider the thickness of 'invisible' soft tissues, using as reference geometry a representation of the underlying generic bones.
b) Experimental marker: despite indications and protocols, it is well known that the identification of repere points [9] is affected by both intra and inter-operator differences [22].

2.2. OpenSim scale tool

The proposed tool consists of a MATLAB script that exploits OpenSim API functionalities (4.3 Version). It was developed on the basis of the OpenSim scale tool, described in the online documentation [23] and summarized in the current sections.

The basic OpenSim scaling procedure takes in input three files: the generic unscaled model file containing the generic set of markers (*GM.osim*), the acquisition of the standing subject (*Static.trc*) and the scaling setup file containing the measurement sets and the marker weights defined by the user (*Setup.xml*). The output of the tool is the scaled model (*SGM.osim*), as shown in Fig. 2.

The GM (*GM.osim*) is one of the models distributed with OpenSim, (e.g. Gait2354, FullBodyModel, etc), which has to be scaled to match the subject geometrical size.

The *Static.trc* file contains the trajectories of the markers in the static

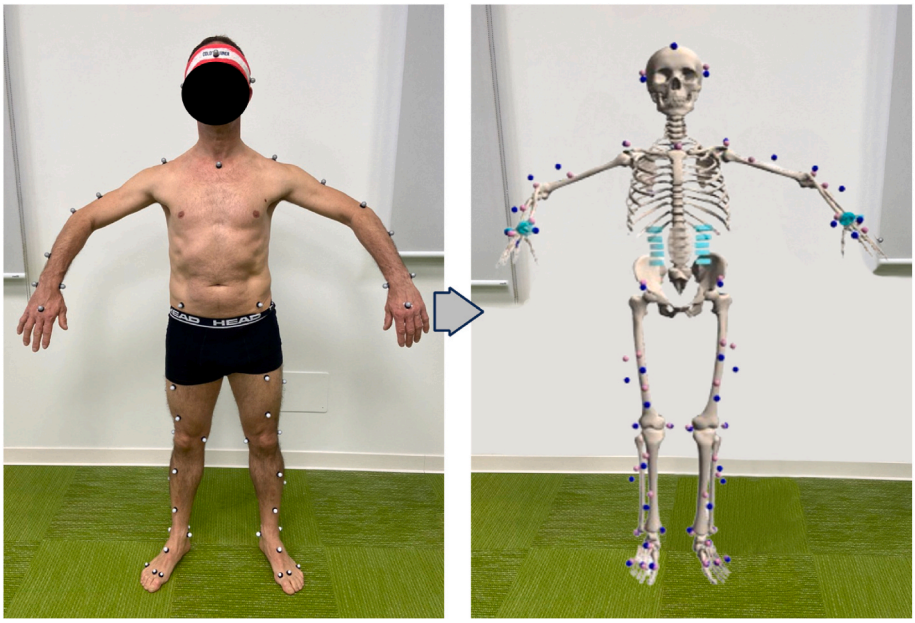

Fig. 3. On the left: the acquired subject instrumented with markers according to a specific protocol; on the right: the scaled MSK model (SGM.osim) of the subject with the superposition of virtual (pink) and experimental (blue) markers.

pose as acquired in a laboratory with an optical system for measurement-based scaling.

The setup file (*Setup.xml*) contains the key assumption for the operation: the measurement set for the estimation of the segment scale factors (SSFs) and eventually the manual scale factors.

As detailed in Fig. 2, after the first scaling step in which the SSFs are computed and the dimensions of the segments are scaled, an inverse kinematic (IK) analysis on the static pose and the marker adjusting is performed as well. The first one calculates the values of DoFs that configure the scaled model in the static pose of the subject; it is used (before adjusting) to check the quality of the scaling results [24] in terms of both RMSE and maximum error since it provides discrepancies between experimental and virtual markers. Iteratively, virtual marker locations have to reasonably be relocated to match experimental marker locations and, thus, to lower the associated errors by attaining the most satisfactory scaling factors.

It is worth reminding that IK results are operator-dependent since the user must select markers and attribute them a weight applied in the formulation of the minimization problem of weighted distances between experimental and model markers whose output is the model joint coordinates. The OpenSim scaling documentation [25] suggests assigning a higher weight value to anatomical markers whose position is better known. Ultimately, adjusting markers causes virtual markers to overlap with experimental ones, which is beneficial for accurately positioning virtual markers not located at anatomical landmarks.

Besides the geometrical properties, the Scaling tool accordingly modifies some muscle-tendon parameters which consist of the optimal muscle fibre length and the tendon slack length; this is computed by proportionally changing their value and the origin and insertion of muscles together with their wrapping constraints.

Although the Scaling tool is mainly focused on linear measurements, the inertial tensor is computed as well after the evaluation of the segment mass. The user has different options, described in [24] for example, she/he can choose to scale the segment mass by checking the "preserve mass distribution during scaling" option, meaning the retention of the original mass distribution while neglecting the effect of the scaling factors.

2.3. Automated scaling tool (AST)

The proposed tool aims to replace the user in the above-described iterative process through an algorithm that cyclically executes the complete scaling procedure, defining instructions and criteria for its quality assessment.

2.3.1. Input

The input files of the AST are the same as the OpenSim tool (Fig. 3): the generic OpenSim model (*GM.osim*), the static pose trial (*Static.trc*), the user-defined scaling setup file (*Setup.xml*). As numerical input, the user is requested to insert, inside the MATLAB input section of the tool, the subject (h_s) and model height (h_m) other than the model and subject weight (this last also foreseen by the manual procedure). Other settings could be settled by the user, such as the threshold values of:

- maximum number of iterations (MaxIter), set by default to 400 as a trade-off between computational timing and results accuracy;
- maximum marker RMSE (EndErr), with a default value equal to 0.003 m which defines a markedly high level of scaling accuracy;
- minimum marker RMSE for forcing not marker-based SSF called "manual" SSF (ManSc); the default value set to 0.025 m points out the threshold of a general misposition of virtual markers, as listed by the OpenSim best practice.

2.3.2. Average scale factor and scaling factor range

The average scale factor (ASF) is determined using the following relation:

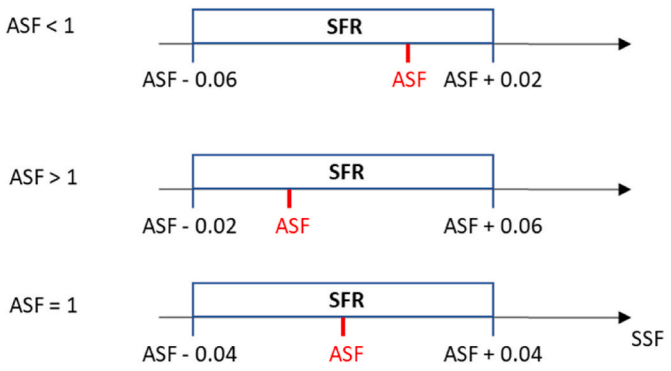

Fig. 4. The scaling factor range (SFR) has asymmetrical boundaries whether the ASF (Average Scale Factor) is lower or higher than 1; whilst SFR is symmetrical when the ASF is equal to 1. The SFR is 8 % of the GM height wide.

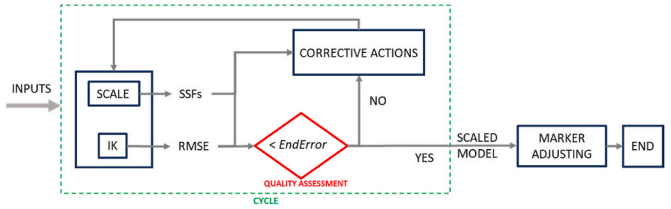

Fig. 5. Workflow of AST: it iteratively executes the scaling and IK of the static pose and performs corrective action whether the RMSE does not fulfil the quality check. If the result of the quality assessment is positive, the tool scales and adjusts the markers on the model.

$$ASF = \frac{h_s}{h_m} \tag{6}$$

and is used to prevent unrealistic results for the segment scale factors. Indeed, it is expected that the SSFs do not differ markedly from the ASF but remain within a prescribed range (SFR) to account for realistic variability among the dimensions of the subject bones. The amplitude of the range was set equal to 0.08 (8 % of the unitary SSF), distributed asymmetrically with respect to the ASF value and differently for ASF>1 ([ASF-0.02 ASF+0.06]) or ASF<1 ([ASF-0.06 ASF+0.02]) (Fig. 4). The so-implemented asymmetry stresses the feature to incur an augmented enlargement or shrinkage of the model segments with respect to the ASF when the subject is taller or lower than the unscaled model, respectively. Whether the ASF is equal to 1, the SFR becomes symmetrical with respect to the ASF spanning in the range [ASF-0.04 ASF+0.04] (Fig. 4). Therefore, the SFR represents the best trade-off between the variability of subject segment lengths and the reliability of marker placement: if the range is too wide, any misplaced marker would not be detected whilst if it is too narrow, every segment would be scaled adopting the ASF. In other words, SFR acts as a spatial constraint on the virtual marker positions, and whether their placement cannot be considered reliable.

2.3.3. Scaling assessment

The first cycle runs the scaling and inverse kinematics (without marker adjusting) applying the user setup file. At the end of the first cycle, as well as at the end of each cycle, the tool performs a check for scaling assessment based on the calculated SSFs and markers RMSE from IK, that is:

$$RMSE \leq EndError \tag{7}$$

If the condition is fulfilled, the tool exits from the cycle, executes the markers adjusting and saves the scaled model (Fig. 5). On the other hand, if the RMSE is higher than the prescribed threshold, corrective actions are applied before repeating the cycle.

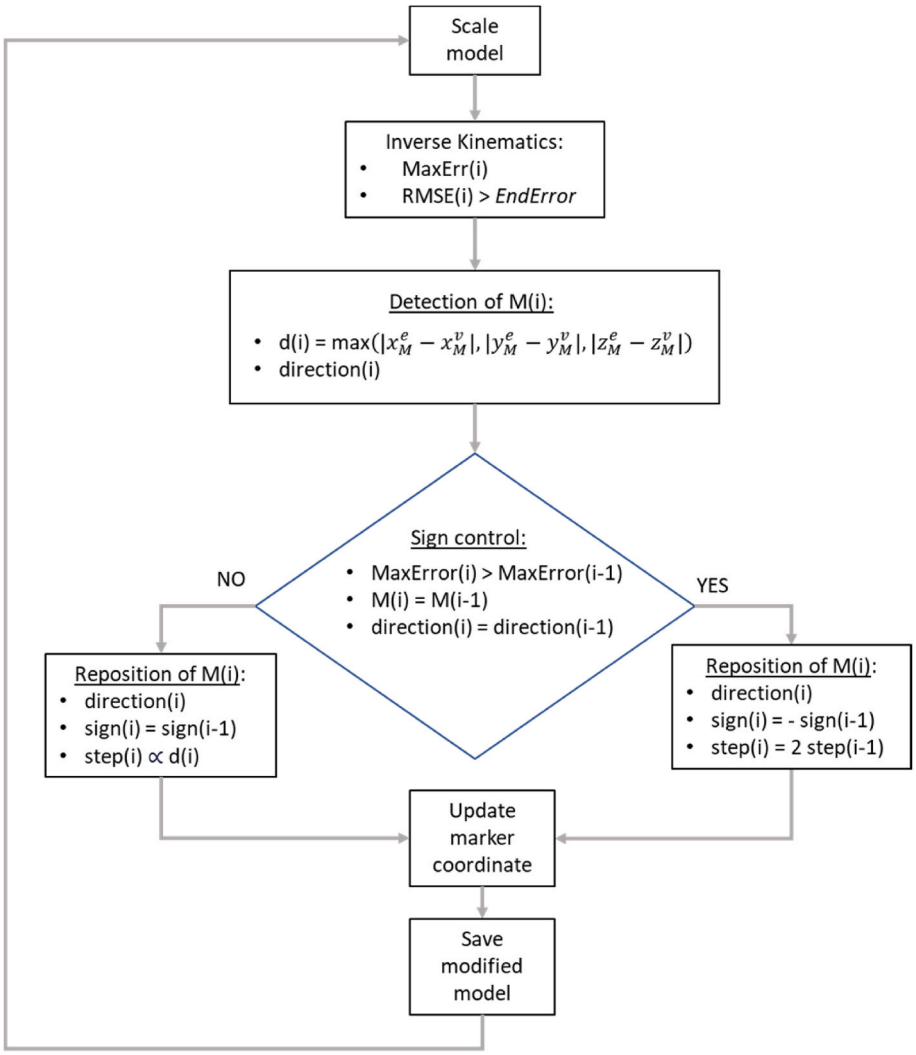

Fig. 6. Scheme of the corrective actions to apply to the most displaced marker coordinate: at each iteration (i) the virtual marker with the highest Inverse Kinematics (IK) error (M) is identified and adjusted proportionally to the error for one coordinate per cycle (d). The sign of the displacement is initially negative and changes if consecutive iterations show an increasing trend in maximum error at the same marker and in this case the displacement magnitude is twice that of the previous iteration, with the same sign, to enhance the correction step.

2.3.4. *Corrective actions*

To achieve the desired scaling quality, the proposed tool performs some corrective actions that replicate what is manually done by the operator on the GM virtual markers. Indeed, while in ideal conditions virtual and experimental markers are perfectly positioned on the model and on the subject, in a more realistic case they can be misplaced. To reduce discrepancies between ideal and real marker placement and improve the scaling quality, at each iteration *i* the virtual marker with the highest IK error (*M*) is identified and "moved" of an amount proportional to the error itself (Fig. 6). The displacement is applied for only one coordinate for cycle, the one with the highest error (*d*):

$$d(i) = max\left(\left|x_M^e - x_M^v\right|, \left|y_M^e - y_M^v\right|, \left|z_M^e - z_M^v\right|\right) \quad (8)$$

where x_M^e, y_M^e *and* z_M^e are the coordinates of the experimental marker, and x_M^v, y_M^v *and* z_M^v those of the virtual one.

The sign of the displacement is set to negative at the first iteration and it is changed whether for two consecutive iterations (cycles *i* and *i-1*) the maximum error (MaxErr) is registered at the same marker with an increasing trend (rather than diminishing). Simultaneously, the module of the displacement (*step*) at the current iteration becomes twice the one considered in the previous iteration (with the erroneous sign) to properly implement the correction step of the previous iteration. So, the sign and correction step at the current iteration becomes:

$$sign(i) = -sign(i-1) \quad (9)$$

$$step(i) = 2\, step(i-1) \quad (10)$$

The marker displacement is defined in the absolute coordinate system for consistency. Then, the new marker coordinate, converted in the segment coordinate system, is saved and used in the next cycle for scaling and IK.

The tool automatically creates the necessary setup files at the beginning of the analysis and updates them throughout the cycles according to the quality check assessment (Fig. 7).

The relocation of the marker *M*, with the aim to increase consistency between the coordinates systems of GM and the experimental data [26], can be executed on *GM_pose.osim* (if chosen in the AST input section) which mimics the experimental pose by importing the DoFs found through IK of the static pose using the respective GM scaled with all SSFs equal to ASF (Fig. 7).

A control is performed on the RMSE value, compared to the threshold of not marker-based scaling procedure (ManSc). If $RMSE \geq ManSc$, meaning that all the markers are mispositioned from the actual locations, the manual scaling setup file (*ManualScale.xml*) will be executed

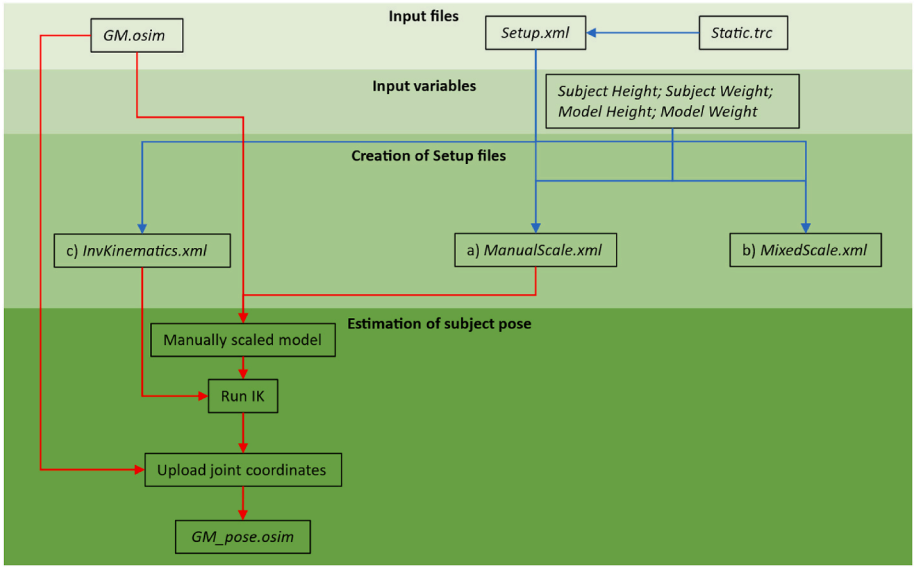

Fig. 7. Automatic creation of setup files (blue arrows) and estimation of subject initial pose (red arrows) from the input files and variables.

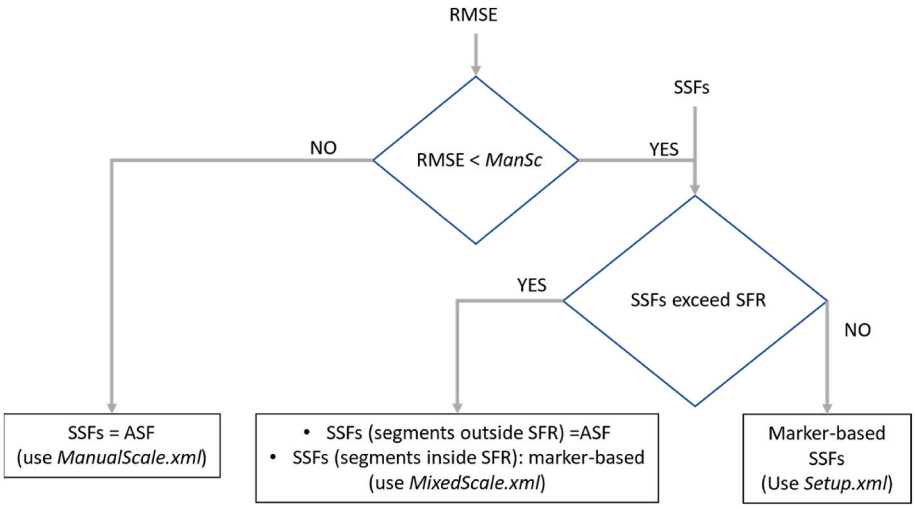

Fig. 8. Automatic creation of the setup file for the three different scaling methodology (manual, marker-based and blended) of a GM depending on the RMSE and SSFs values.

Table 1
Resume of the GMs used for the AST validation; each model/subject differs in terms of number of degrees of freedom, number of segments, number of adopted markers, height and weight.

Subject	GM	DoFs	# Segments	# Markers	Model Mass [kg]	Model Height [m]	Subjet Mass [kg]	Subject Height [m]
1	G23 M	23	14	20	75.16	1.8	85	1.65
2	FBM	37	22	37	75	1.7	75	1.80
3	TLM	111	78	55	78	1.75	65	1.65

For each model and markerset, 10 different initial locations of the virtual markers were manually generated as to simulate a user-dependent procedure and labelled in the following as VM.

where all the segments are assigned the ASF. This operation will force the markers to be placed in a more plausible location. Differently, if $RMSE \leq ManSc$, two options are available, depending on the values of the SSFs: if these last remain within the above introduced reasonable range, SFR, the initial scaling setup file is used *(Setup.xml)*. Otherwise, if the check on SSF detects some values outside the range, a blended scaling method *(MixedScale.xml)* is chosen: while marker-based measurement is adopted for the segments with $SSF \in SFR$, the ASF is applied to the out-of-range ones (Fig. 8).

2.4. Test cases

In this section, we describe the application of the AST to three cases differing for the generic model, experimental markerset and subject (Table 1). Additionally, for each case, ten initial virtual marker locations were predefined. Results are reported in terms of errors, iterations and

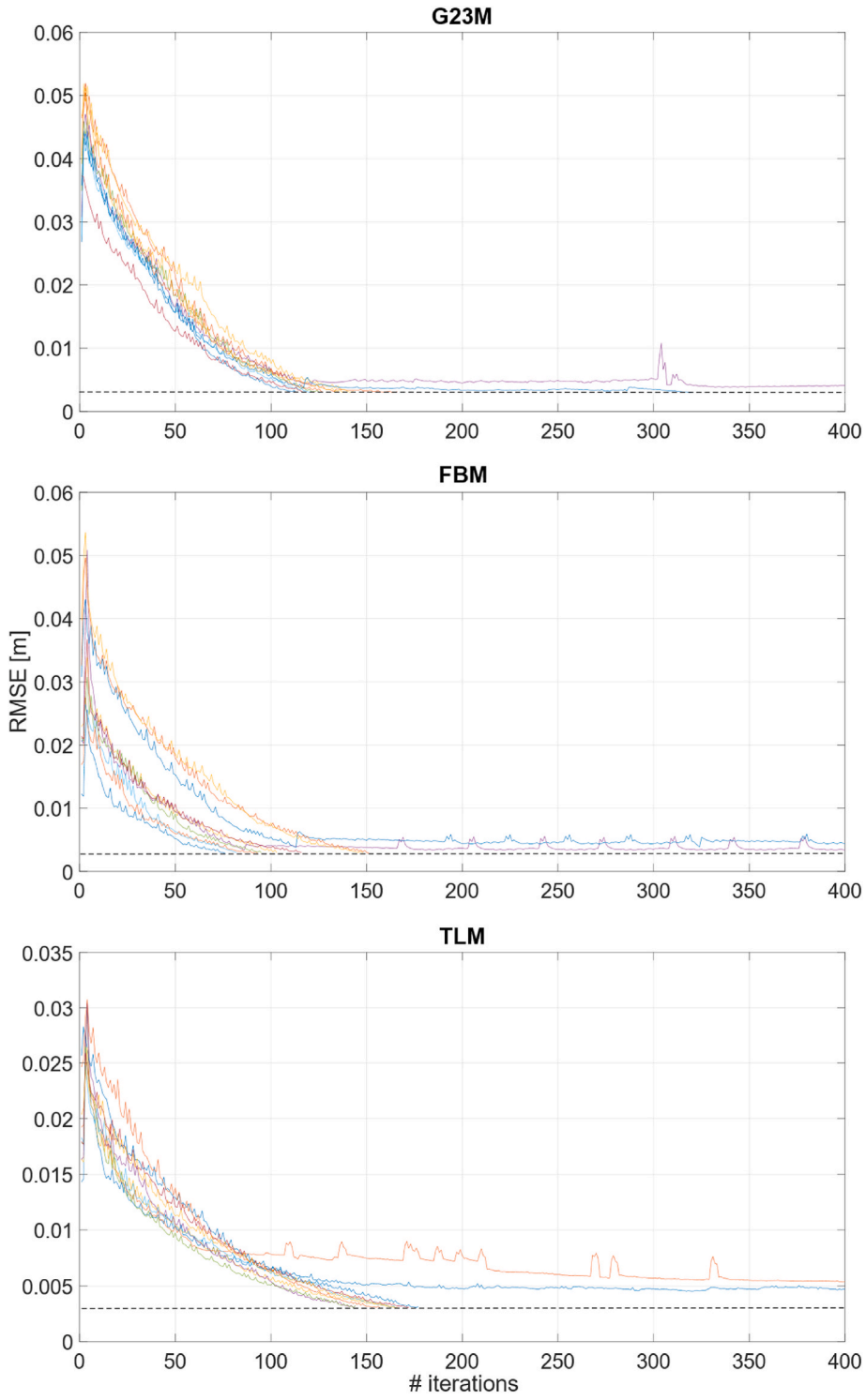

Fig. 9. Markers RMSE curve over scaling iterations for the 10 different VM configurations for each of the three GM models considered. The dashed line points out the threshold of accuracy set by the user.

required CPU time.

2.4.1. Experimental data

The tool was tested on two different data sources:

a) experimental MoCap data collected at the Biomechanics Laboratory of the "Sport and Anatomy Centre" of the University of Pisa (where a Vicon motion analysis system with eight infrared cameras @100 Hz is installed) and

b) public domain data of the Knee Grand Challenge Competition [26].

Totally, three male subjects were selected: subject 1 (60 y.o, 1.65 m, 65 kg) and subject 3 (68 y.o, 1.68 m, 85 kg) acquired at the "Sport and Anatomy Centre" and subject 2 (86 y.o., 1.8 m and 75 kg) which is the captured subject of the 5th Knee Grand Challenge competition. The experimental markerset differed from model to model: subject 1 was recorded using Lower Body Plug-in-Gait [19,27] markerset composed of 20 markers, subject 2 consisted of KGC 5th edition public domain

Table 2
Summary of scaling process results for the different VM configurations for the three GM models.

VM	I. RMSE [m]	F. RMSE [m]	CPU time [s]	Iterations #
G23 M 1	0.026802	0.002993	157	112
G23 M 2	0.04039	0.002975	201	165
G23 M 3	0.039168	0.002951	200	142
G23 M 4	0.030760	0.004122	438	400
G23 M 5	0.034894	0.002996	188	125
G23 M 6	0.027680	0.002974	143	120
G23 M 7	0.037315	0.002982	136	116
G23 M 8	0.035753	0.002977	348	319
G23 M 9	0.046424	0.002928	135	126
G23 M 10	0.046703	0.002930	143	138
FBM 1	0.012292	0.002889	334	74
FBM 2	0.016900	0.002881	795	91
FBM 3	0.022959	0.002974	910	101
FBM 4	0.020785	0.003401	3685	400
FBM 5	0.021159	0.002959	450	93
FBM 6	0.020513	0.002979	374	80
FBM 7	0.02137	0.002976	500	114
FBM 8	0.030769	0.004399	3595	400
FBM 9	0.032558	0.002911	1320	149
FBM 10	0.039715	0.002913	1330	146
TLM 1	0.014326	0.004746	6779	400
TLM 2	0.019215	0.005350	11349	400
TLM 3	0.016368	0.002967	17540	165
TLM 4	0.016345	0.002989	11027	143
TLM 5	0.017803	0.002981	10077	143
TLM 6	0.018293	0.002961	11777	164
TLM 7	0.017923	0.002994	16916	171
TLM 8	0.025673	0.002983	13132	176
TLM 9	0.024652	0.002954	17137	156
TLM 10	0.020360	0.002999	17883	164

dataset (consisting of 37 markers) and subject 3 was acquired using the more sophisticated CGM 2.5 FullBodyModel [28] model which included 55 markers.

The scaling procedure was executed considering the data of the static pose while the validation of the scaling results was performed on complete walking trials for each of the investigated subject.

2.4.2. MSK models

In the AST validation process, three among the most frequently used MSK models were considered: a) the Gait2392 model [29–32] (G23 M) to represent the subject 1 b) the FullBodyModel model [33] (FBM) used to represent the subject 2, and c) the Thoracolumbar model [34](TLM) adopted to represent the subject 3, and scaled with the above mentioned experimental dataset. These three models differ for size, degrees of freedom (DoFs), number of segments and markerset, as shown in Table 1.

2.4.3. Scaling settings and outputs

The tool settings fixed the target RMSE (EndError) at 0.003 m and the maximum number of iterations (MaxIter) at 400.

As reference case, a scaled model was defined by a 2.5-years of OpenSim-skilled operator for each type model/subject and VM.

3. Results

As results of the application of the AST, the plots of the RMSE iteration during the process (Fig. 9) and a table comparing initial and final RMSE (I. RMSE and F. RMSE), the computational time and the number of completed iterations (Table 2) are reported for each VM. Additionally, the IK RMSEs obtained in the dynamic task (gait) with the scaled models are detailed in Fig. 10.

3.1. Scaling RMSE

The RMSE of the marker positions in the static pose is shown in Fig. 9 for all the simulated cases. For each model type, the plots show a decreasing trend of the RMSE in an exponential-like law as cycles are repeated and iterations increase. However, small fluctuations are present due to the change of sign during marker relocation and to the change of scaling methodology (manual, marker-based, blended) as explained in Fig. 8.

As the G23 M model is concerned, 9 out of 10 runs achieved the required threshold (3 mm) in less than 400 iterations. As an overall evaluation, the initial average RMSE was 36.59 mm (±6.94 mm), while it decreased to 3.08 mm (±0.36 mm) at the end of the process, indicating a reduction of 1187 %. The average elapsed time was 209 s and 178 iterations. In the worst case, the final RMSE was 4.12 mm. after 400 iterations completed in 438 s.

Similarly, scaling the FBM produced an average final RMSE of 3.13 mm (±0.47 mm) against an initial value of 23.90 mm (±8.11 mm) with an improvement of 776 %. In two cases the tool did not reach the required threshold in 400 iterations; in the worst case the final RMSE was 4.4 mm, and the average CPU time was 1330 s (ca 22 min).

Finally, the 10 VM cases for the TLM model were scaled obtaining a final RMSE equal to 3.39 mm (±0.88 mm) starting from an average value of 19.10 mm (±3.61 mm). Thus, a percentage RMSE improvement of 563 % was reached.

In two occurrences the tool completed the 400 iterations with an RMSE higher than 3 mm. (i.e. 4.75 and 5.35 mm). The average elapsed time was 13362 s (i.e. 3.7 h). All the simulations were performed using an Intel (R) Core(TM) i7-10875H CPU @ 2.30 GHz PC with 32 GB RAM installed.

3.2. Tool validation

The advantages of using the AST were further investigated by completing the inverse kinematic analysis of a gait cycle with the scaled models (Fig. 10). The RMSE of the gait IK was evaluated at every time increment. Thus, results are reported as box plot of the collected values over the gait cycle and compared to those obtained using the operator-scaled model.

In this case, the average gait RMSE for the G23 M was 8.5 mm (±0.76 mm) against the 44.3 mm (±7.5 mm) obtained with the model scaled by the operator; higher values were found for the FBM: 10.7 mm (±1.5 mm) against 26.6 mm (±4.3 mm). The TLM also in this case yielded the highest RMSE: 14.3 mm (±3.9 mm) while for the reference model was 23.3 mm (±4 mm).

4. Discussion and conclusions

The present paper proposes an automatic tool for scaling OpenSim generic models using marker data. It improves the scaling procedure replacing the operator in iteratively modifying the marker locations of the GM to reduce marker position errors. In this way, the process is more reliable and less time-consuming.

A general overview of the flowchart was described and the application to three different models and datasets was reported and compared to results obtained using a model scaled by an expert operator. In all the cases, this innovative tool showed encouraging results by providing reliable scaled MSK models in relatively brief times: within the scaling process, the tool achieves a reliable level of accuracy [11] after less than 100 iterations for each of the models considered.

The execution times spanned from a few minutes to a few hours, depending on the complexity of the model, i.e. Dofs and number of markers. Anyway, it was much less than the time required by the user for the manual procedure. More importantly, the RMSE of the static IK obtained with the tool was one order of magnitude smaller than the one obtained by the operator. In most of the analyses, the models were

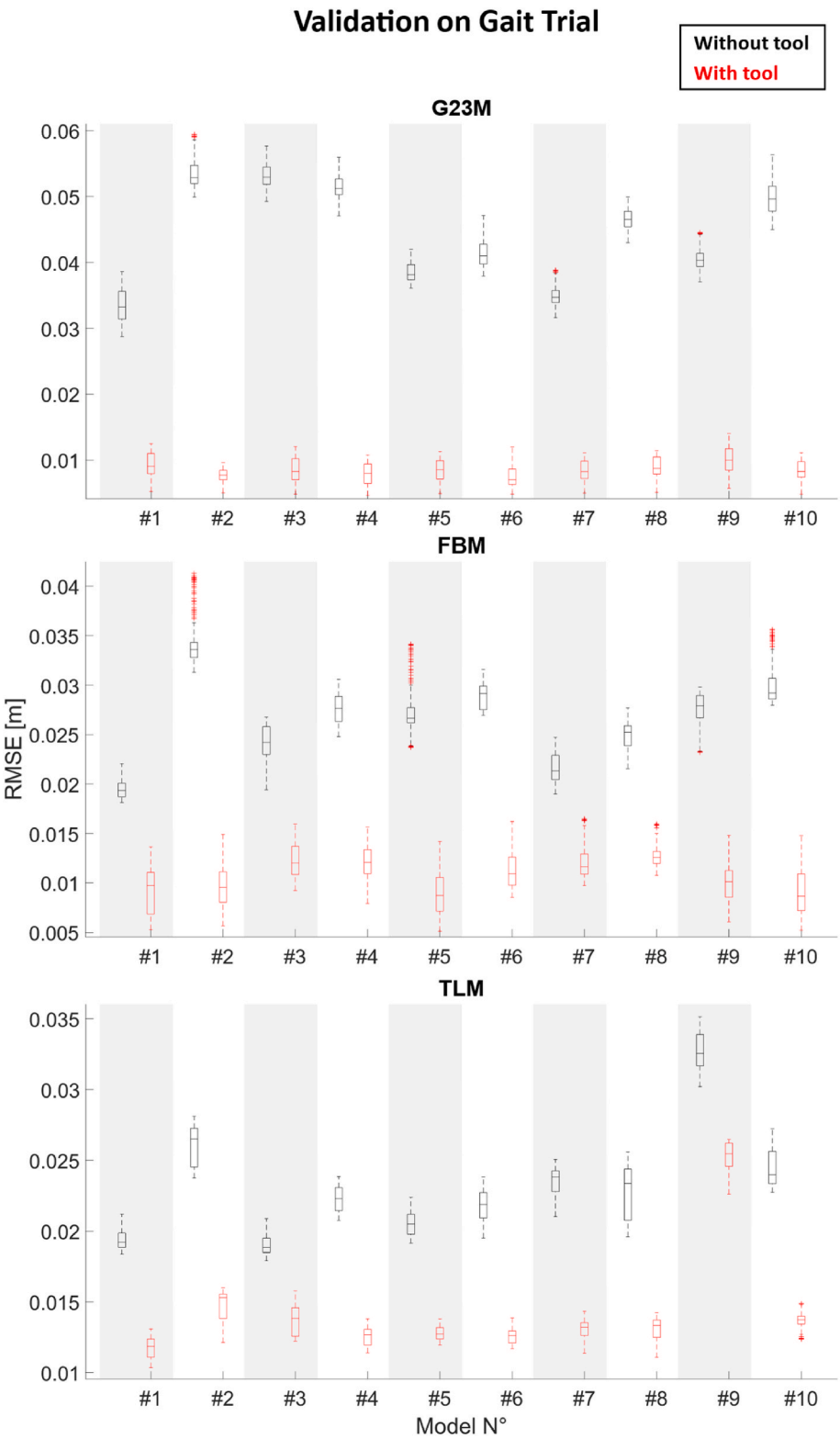

Fig. 10. Boxplots of Gait IK marker RMSE of both manually scaled (black) and AST scaled models (red).

scaled achieving the RMSE threshold of 3 mm within 400 iterations as required by the user. However, the maximum RMSE was 5.35 mm which is very low considering that the best practices of OpenSim suggest 10 mm [11]. Interestingly, the final RMSE did not depend on its "initial" value, i.e. on the initial virtual marker locations. Therefore, when preparing the markerset file for the GM, the user is not required to pay extreme attention to marker placement, as the tool will compensate for small misplacements.

Higher RMSE values were observed in the IK results of the gait cycle than in the static trial. These errors could depend on the GM in terms of DoFs and range of motion.

Regarding the small fluctuations observed in the decreasing trend of the RMSE of the marker positions in the static pose (Fig. 9), these may be attributed to the algorithm's initial estimation of a correction term

(absolute value) to be added to the coordinate of the most displaced marker. To resolve the indeterminacy of the direction, the algorithm initially assigns a negative sign to the correction term. Subsequently, the quality assessment mechanism verifies if the chosen direction was correct; if not (indicating a global peak), the tool adjusts in the subsequent iteration by changing the sign of the marker coordinate correction. Although RMSE peaks occur consistently throughout the simulation, it is important to note that they tend to be higher at the beginning due to the initially higher correction terms.

It is important to underline that any error in the scaling process, that stands at the beginning of an MSK analysis, propagates through the subsequent steps and can result in model inconsistencies such as incorrect joint angles and residual forces. In this study, the advantageous use of the AST was proved in performing gait IK with automatically scaled models. The RMSE was reduced 5, 2.5 and 1.6 times for the G23 M, FBM and TLM respectively, that is IK results improved more for simpler models.

It is dutiful to acknowledge the limitations of our proposed methodology. Firstly, the AST tool relies on the correct configuration of the OpenSim API environment through Matlab as it is not a standalone software at present. Secondly, the tool still requires manual intervention from the user to provide a scaling setup file with as much accuracy as possible since this is essential for achieving the most precise scaling results.

Nevertheless, the user is only required to add fewer settings than the predefined Opensim Scaling tool, such as the threshold RMSE (maximum acceptable value) and the maximum number of iterations. The operator can also make manual changes to the initial marker set to improve the results. Furthermore, it is dutiful to observe that the precision achieved in the outcomes is affected by the model pose in the static trial, which can be defined by the user or estimated by the tool. The second option was adopted for the above-described results but in some cases, the intervention of the user in this step could further improve solutions.

Moreover, we strongly advise users not to solely rely on the numerical value of the displayed error for result evaluation. Instead, we recommend visually inspecting the output model using the OpenSim GUI and adhering to the guidelines provided by the OpenSim developers, even when utilizing this tool [11]. Shortly, we plan to extensively employ this tool on a wider range of subjects and MSK models especially to include female participants by launching AST in combination with generic female MSK models [34]. Simultaneously, we encourage members of the biomechanical community to provide feedback to ensure its ongoing effectiveness.

In conclusion, this developed and freely available tool has the potential to benefit the entire biomechanical community for scaling quickly and accurately GMs as it is a first fundamental step for MSK analyses both in research and in clinical applications.

Funding acquisition

Research partly funded by PNRR - M4 C2 - Investimento 1.5, Creazione e rafforzamento di “ecosistemi dell’innovazione”, costruzione di “leader territoriali di R&S”, funded by the European Commission under the NextGeneration EU programme, project "THE" subproject 6.

CRediT authorship contribution statement

Andrea Di Pietro: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alex Bersani:** Writing – review & editing, Validation, Supervision, Software. **Cristina Curreli:** Writing – review & editing, Validation, Supervision, Resources. **Francesca Di Puccio:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgments

The authors wish to sincerely thank Rosanna Viglialoro, Antonia Centrone and Lorenza Mattei for their technical support in the experimental activities.

References

[1] A.D. Sylvester, S.G. Lautzenheiser, P.A. Kramer, A review of musculoskeletal modelling of human locomotion, Interface Focus 11 (5) (2021) 20200060.
[2] C. Curreli, F. Di Puccio, G. Davico, L. Modenese, M. Viceconti, Using musculoskeletal models to estimate in vivo total knee replacement kinematics and loads: effect of differences between models, Front. Bioeng. Biotechnol. 9 (2021).
[3] R. Akhundov, D.J. Saxby, L.E. Diamond, S. Edwards, P. Clausen, K. Dooley, S. Blyton, S.J. Snodgrass, Is subject-specific musculoskeletal modelling worth the extra effort or is generic modelling worth the shortcut? PLoS One 17 (1) (2022) e0262936.
[4] S. Martelli, G. Valente, M. Viceconti, F. Taddei, Sensitivity of a subject-specific musculoskeletal model to the uncertainties on the joint axes location, Comput. Methods Biomech. Biomed. Eng. 18 (14) (2015) 1555–1563.
[5] G. Valente, G. Crimi, N. Vanella, E. Schileo, F. Taddei, nmsBuilder: freeware to create subject-specific musculoskeletal models for OpenSim, Comput. Methods Progr. Biomed. 152 (2017) 85–92.
[6] W. Koller, A. Baca, H. Kainz, Impact of scaling errors of the thigh and shank segments on musculoskeletal simulation results, Gait Posture 87 (2021) 65–74.
[7] J.J. Dunne, T.K. Uchida, T.F. Besier, S.L. Delp, A. Seth, A marker registration method to improve joint angles computed by constrained inverse kinematics, PLoS One 16 (5) (2021) e0252425.
[8] M. Tomasi, A. Artoni, L. Mattei, F. Di Puccio, On the estimation of hip joint loads through musculoskeletal modeling, Biomech. Model. Mechanobiol. 22 (2) (2023) 379–400.
[9] T. Uchida, A. Seth, Conclusion or illusion: quantifying uncertainty in inverse analyses from marker-based motion capture due to errors in marker registration and model scaling, Front. Bioeng. Biotechnol. 10 (2022) 874725.
[10] S.L. Delp, F.C. Anderson, A.S. Arnold, P. Loan, A. Habib, C.T. John, E. Guendelman, D.G. Thelen, OpenSim: open-source software to create and analyze dynamic simulations of movement, IEEE Trans. Biomed. Eng. 54 (11) (2007) 1940–1950.
[11] J.L. Hicks, T.K. Uchida, A. Seth, A. Rajagopal, S.L. Delp, Is my model good enough? Best practices for verification and validation of musculoskeletal models and simulations of movement, J. Biomech. Eng. 137 (2) (2015) 209051–2090524.
[12] J.A. Reinbolt, J.F. Schutte, B.J. Fregly, B.I. Koh, R.T. Haftka, A.D. George, K. H. Mitchell, Determination of patient-specific multi-joint kinematic models through two-level optimization, J. Biomech. 38 (3) (2005) 621–626.
[13] I.W. Charlton, P. Tate, P. Smyth, L. Roren, Repeatability of an optimised lower Body model, Gait Posture 20 (2) (2004) 213–221.
[14] K. Werling, N.A. Bianco, M. Raitor, J. Stingel, J.L. Hicks, S.H. Collins, S.L. Delp, C. K. Liu, AddBiomechanics: Automating Model Scaling, Inverse Kinematics, and Inverse Dynamics from Human Motion Data through Sequential Optimization, 2023, 2023.06.15.545116.
[15] A. Cappozzo, A. Cappello, U. Della Croce, F. Pensalfini, Surface-marker cluster design criteria for 3-D bone movement reconstruction, IEEE Trans. Biomed. Eng. 44 (12) (1997) 1165–1174.
[16] A. Leardini, F. Biagi, A. Merlo, C. Belvedere, M.G. Benedetti, Multi-segment trunk kinematics during locomotion and elementary exercises, Clin. Biomech. Bristol Avon 26 (6) (2011) 562–571.
[17] A. Leardini, Z. Sawacha, G. Paolini, S. Ingrosso, R. Nativo, M.G. Benedetti, A new anatomically based protocol for gait analysis in children, Gait Posture 26 (4) (2007) 560–571.
[18] A. Leardini, M.G. Benedetti, L. Berti, D. Bettinelli, R. Nativo, S. Giannini, Rear-foot, mid-foot and fore-foot motion during the stance phase of gait, Gait Posture 25 (3) (2007) 453–462.
[19] R.B. Davis, S. Õunpuu, D. Tyburski, J.R. Gage, A gait analysis data collection and reduction technique, Hum. Mov. Sci. 10 (5) (1991) 575–587.
[20] S. Armand, M. Sangeux, R. Baker, Optimal markers’ placement on the thorax for clinical gait analysis, Gait Posture 39 (1) (2014) 147–153.
[21] A. Leardini, Z. Sawacha, G. Paolini, S. Ingrosso, R. Nativo, M.G. Benedetti, A new anatomical based protocol for gait analysis in children, Gait Posture 26 (2007) 560–571.
[22] C. Bishop, D. Thewlis, H. Uden, D. Ogilvie, G. Paul, A radiological method to determine the accuracy of motion capture marker placement on palpable anatomical landmarks through a shoe, Footwear Sci. 3 (3) (2011) 169–177.
[23] The Scale Tool: Evaluating the Results, 2011.
[24] Scaling - OpenSim Documentation - Global Site” [Online]. Available: https://simtk-confluence.stanford.edu:8443/display/OpenSim/Scaling.
[25] Checklist - Evaluating Your Simulation - OpenSim Documentation - Global Site” [Online]. Available: https://simtk-confluence.stanford.edu:8443/display/OpenSim/Checklist+-+Evaluating+your+Simulation.

[26] B.J. Fregly, T.F. Besier, D.G. Lloyd, S.L. Delp, S.A. Banks, M.G. Pandy, D.D. D'Lima, Grand Challenge competition to predict in vivo knee loads, J. Orthop. Res. 30 (4) (2012) 503–513.
[27] D. Winter, Biomechanics and motor control of human movement. , 1990 [Online]. Available: https://www.semanticscholar.org/paper/Biomechanics-and-Motor-Control-of-Human-Movement-Winter/38eeb17eff429b02c48b15af52c277fe7e5507ce.
[28] F. Leboeuf, R. Baker, A. Barré, J. Reay, R. Jones, M. Sangeux, The conventional gait model, an open-source implementation that reproduces the past but prepares for the future, Gait Posture 69 (2019) 235–241.
[29] F.C. Anderson, M.G. Pandy, A dynamic optimization solution for vertical jumping in three dimensions, Comput. Methods Biomech. Biomed. Eng. 2 (3) (1999) 201–231.
[30] F.C. Anderson, M.G. Pandy, Dynamic optimization of human walking, J. Biomech. Eng. 123 (5) (2001) 381–390.
[31] S.L. Delp, J.P. Loan, M.G. Hoy, F.E. Zajac, E.L. Topp, J.M. Rosen, An interactive graphics-based model of the lower extremity to study orthopaedic surgical procedures, IEEE Trans. Biomed. Eng. 37 (8) (1990) 757–767.
[32] G.T. Yamaguchi, F.E. Zajac, A planar model of the knee joint to characterize the knee extensor mechanism, J. Biomech. 22 (1) (1989) 1–10.
[33] A. Rajagopal, C.L. Dembia, M.S. DeMers, D.D. Delp, J.L. Hicks, S.L. Delp, Full-body musculoskeletal model for muscle-driven simulation of human gait, IEEE Trans. Biomed. Eng. 63 (10) (2016) 2068–2079.
[34] A.G. Bruno, M.L. Bouxsein, D.E. Anderson, Development and validation of a musculoskeletal model of the fully articulated thoracolumbar spine and rib cage, J. Biomech. Eng. 137 (8) (2015) 810031–8100310.