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STRENGTH MAPPING ALGORITHM (SMA) FOR BIOMECHANICAL HUMAN MODELLING USING EMPIRICAL POPULATION DATA

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Abstract

Despite the increasing level of detail in biomechanical simulation, human models are not yet valid to represent specific individuals or populations. Therefore, the generic models need adaptation to depict the varying competencies of the respective person or user group aimed to investigate. There have been achievements in scaling single modelling domains (e.g. anthropometry). However, a comprehensive approach is still lacking. This paper extends available methods by introducing a Strength Mapping Algorithm (SMA) for the adaption of individual maximum isometric forces to match empirical strength data. This procedure involves static optimization simulation of predefined body postures to reveal the dependencies between muscle forces and joint torques of a generic model specifying the skeletal and muscular geometry. Based on this information, we determine a set of muscle scaling factors for a given age, gender and strength percentile. As a result, the SMA enables the quick generation of a large number of individuals in order to implement a design for populations paradigm. This leads one step closer to gain deeper insight on how health relevant products and processes are to be developed.

Keywords: User centred design, Human factors engineering, Simulation, Virtual engineering (VE), Strength percentiles

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1 INTRODUCTION

The multidisciplinary field of user-centred design tries to specify product characteristics to meet the requirements and wishes of prospective users (e.g. usability, comfort, joy of use). The overall goal is to develop products and processes usable by people with different capabilities and needs. Those can range from working tools and tasks through mobility products to sporting equipment, wherever interactions with humans exist. Due to the demographic change, there is a rising heterogeneity of human competencies in developed societies. The creation of innovative user-centred technology usually requires the extensive and continual use and application of physical prototypes in conjunction with methods of user involvement applied by an interdisciplinary team (Krüger et al., 2014). Unfortunately, in the industrial setting time constraints and lack of experience in these areas often lead to just inadequate consideration of future users. In addition, safety-related issues often cannot be assessed without the risk of injuring real test persons.

As computer-aided engineering methods and tools (e.g. FEM, CFD, 3D inject moulding simulation) are becoming more and more powerful, also new opportunities arise to virtually assess and validate user-dependent product and process properties. The virtual product development approach basically focuses on the computer-aided evaluation and validation of the consequences of design choices already in the early stages of the product engineering process. If properly implemented, this strategy is capable of cutting development costs by saving physical prototypes and time as well as to increase the final product quality in the same vein. This paradigm can also lead to a more efficient user-centred product and process development as soon as intuitive methods and tools are available to configure and simulate user-product interactions. Therefore, the products as well as the users have to be modelled as accurately as possible with special attention to existing interfaces. Nowadays, the product model is usually available as a three-dimensional representation in CAD (computer-aided design). The level of detail varies along the product engineering process starting from skeleton models to a full documentation of technical drawings. The applied digital human models have to represent the constitution and behaviour of real humans virtually in order to gain insights into the user-product interaction. According to Bubb and Fritzsche (2009) there are models available covering subdivisions of the human body and mind enabling for example anthropometric, anatomical, biomechanical or even cognitive analyses. Although anthropometric models are the most prevalent in industrial practice, especially biomechanical models hold potentials to uncover the ongoing processes in the human body. Despite the increasing level of detail of biomechanical simulations, digital human models do still not allow for representing the specifics of individuals or even populations. The prevalent generic models need adaptation to depict the varying competencies of the person or user group aimed to investigate. This approach supports the virtual implementation of design for populations paradigms like universal design (Story et al., 1998) or mass customization (Gilmore and Pine, 2000). The information extracted from such simulations can assist engineers in the development of health preserving, enhancing or even restoring technology. This in turn can enhance physical and psychological health, which is believed to be a precursor for a contented work life and leisure time increasing the overall quality of life.

Following research questions need to be resolved to fully harness the potentials of biomechanical simulations in product and process development:

1. How can demographically diverse groups of biomechanical models be generated accurately?
2. How can biomechanical models/simulations be integrated with CAD to enable an efficient and intuitive application for design engineers?
3. How can the user-product interaction (incl. user behaviour) be predicted without the need for detailed and extensive observation?
4. How can the performance of biomechanical simulations be improved to enable detailed simulations of parametric product models in conjunction with user groups or whole populations?
5. Which parameters are indicative as predictor for the evaluation of user-dependent product properties using biomechanical simulations and how can these valuation criteria be modelled?

This contribution addresses the first question by introducing a Strength Mapping Algorithm (SMA) for the fast adaption of generic models to match empirical strength data.

2 HUMAN FACTORS ENGINEERING

"Ergonomics or human factors is a body of knowledge about human abilities, human limitations and other human characteristics that are relevant to design. […] Ergonomic design or human factors engineering is the application of ergonomic information to the design of tools, machines, systems, tasks, jobs and environments for safe, comfortable and effective human use." (Chapanis, 1995)

According to the aforementioned definitions digital human models can be seen as virtual human factors tools. The models therefore must contain the human factors information relevant to the present design task. Chapanis (1995) also insists that design engineers cannot work with general guidelines as developing products is much harder than just doing basic research. They rather need specific design recommendations. Only such are sufficiently easy to implement in the product engineering process. Addressing the biomechanical simulation environment, it has to be efficiently applicable in the field of human factors engineering. As biomechanical simulations do not fulfil these requirements so far, intuitive and efficient workflows are to be developed in order to gain the relevant information along the design process.

2.1 Stress and Strain Concept

The stress and strain concept according to Rohmert (1984) is a theoretical approach to describe and analyse the cause-effect relationships between human beings and its environment. In analogy to engineering mechanics, this concept describes the inner reactions of the human body in response to counteract the imposed external conditions fulfilling Newton's laws of motion. In mechanical systems the stresses can be subsumed as all external exposures (e.g. forces acting on a part). In this case the strain is the resulting tension. The tension thereby depends besides the stress level also on the geometry as well as the material properties of the part. In user-centred product and process design, for example physical, chemical, organisational or social stresses can be relevant. The strain is then the psychophysical or behavioural reaction of the human being as a function of the stresses itself as well as its individual competences and capabilities (e.g. training level, habituation). Consequently, the same stress can lead to different strain in different people. The possibilities for a direct measurement of the inner strain conditions are very limited. Nevertheless, there are indicators which allow drawing conclusions on the occurring strain like heart rate, breath rate or muscular activity. (Schlick et al., 2010)

However, a design for populations approach cannot serve with the possibility for comprehensive observations using such indicators in conjunction with real test subjects. This issue can be bypassed by implementing biomechanical simulations into the design process.

2.2 Biomechanical Digital Human Modelling

Biomechanical models contain a skeleton modelled as multi-body system as well as muscles acting as actuators. The underlying simulation systems are able to conduct dynamic analyses of the human musculoskeletal system considering muscle and joint loads as well as neurophysiological reactions. These phenomena can be seen as the ultimate cause of a specific motion behaviour. Biomechanical digital human models are therefore able to reveal the strain imposed on the musculoskeletal system with respect to motion dynamics as well as the stresses acting on the body by external boundary conditions according to the aforementioned stress and strain concept.

Due to the lack of usability and unsolved problems of simulating user-product interactions, biomechanical simulation systems are not very widespread in industry at present. Among other things, issues are for example the representation of the physical interfaces between the users and products as well as the synthetic generation of natural motion behaviours without the need for extensive observation (e.g. motion capturing, electromyography (EMG)). (Miehling et al., 2013b)

The AnyBody Modeling System (Rasmussen et al., 2003) and OpenSim (Delp et al., 2007) are examples for sophisticated biomechanical simulation environments. The supplied musculoskeletal models commonly specify an exemplary average individual. The simulation systems usually contain a scaling tool which allows adjusting the models' size and weight parameters according to manual measurements. This circumstance is due to their origin. Most of these systems were not primarily developed for product development, but rather for clinical applications like the simulation of pathological gait in order to support surgical planning processes (Fox et al., 2009).

To address this issue, we proposed a process for the derivation of parameters crucial for a comprehensive adaption of biomechanical models according to empirical data. (Miehling et al., 2013a) As biomechanical models comprise just a skeleton as well as muscles, we focus on differences in anthropometry as well as motor functions like strength, range of motion and motion speed. The relevant data to consider the heterogeneous competence variations over the human life span are taken from literature.

First of all, we choose **gender** and **age** of the model to be generated according to the target group of the future product or process. In the consecutive steps of the adaption process, percentile values in conjunction with already existing population data are favourable as input to specify the model. However, data from manual measurements can be beneficial to model a specific person or user group.

In most cases, the method of choice for specifying the body measures is to choose percentiles. The **height** and consequently scaling information for the body segments can then be computed using population data, taking into account the specified age and gender. Body height data of one culture and gender can be presumed to follow a normal distribution in most cases. Studies therefore often make the body height distribution of a specific age group and sex available as mean value accompanied by the standard deviation or standard error as for example in the National Nutrition Survey II (NVS II) published by the Max Rubner-Institut (2008). Among others, this representative survey reports the sociodemographic characteristics as well as anthropometric measures of the German population. On this basis, the scaling factors for the body segments are calculated which are eventually used to scale the musculoskeletal model.

After collecting the data for the segmental lengths, we specify the **body weight** of the model to be generated. Even though body weight is usually not normally distributed, the majority of surveys report the weight in the same way as the body height and therefore neglect valuable information about the underlying sample. Moreover, body weight tends to increase with body size. This correlation hampers the computation of the body weight using the body weight distribution of the population. Due to this issue, the present approach uses the body mass index (BMI) instead. Keys (1972) advised the BMI as a measure for the physical constitution of populations. The BMI for a given body weight m and height h follows the equation:

$$BMI = {}^{m}\!/_{h^2} \tag{1}$$

This index removes the dependency between weight and height and is a good predictor for body fat percentage. Hemmelmann (2010) calculated the BMI distribution for both genders and every single year of age using the LMS method based on the raw data of the NVS II. Thereof, the BMI and ultimately the body weight can be calculated taking the specified body height of the preceding step into account. The entire body's mass distribution, respectively the individual body segment weights, is then computed considering the scaling factors for the body part dimensions. If the human model's dimensions are scaled just considering the overall change in body height, the mass distribution stays unaffected.

Thereafter, we adapt the model's **mass moments of inertia** as well as the **range of motion** taking previously calculated parameters into account (e.g. dimensional and weight changes). After scaling the other domains of the model according to empirical data, the maximum **strength** the model is capable to exert has to be adapted. In biomechanical models the strength is usually represented by the maximum isometric forces of the skeletal muscles. These are highly dependent on age, weight and size. In the following chapter we describe the step of adapting this modelling domain in more detail.

3 STRENGTH ADAPTION OF BIOMECHANICAL MODELS

The Strength Mapping Algorithm (SMA) is capable to adapt biomechanical models to match empirical strength data. We demonstrate this using the example of a generic three-dimensional biomechanical leg model.

3.1 Generic Model of the Lower Extremity

The original OpenSim model was developed by Thelen, Seth, Anderson and Delp. Its joint definitions are based on Delp et al. (1990), its anthropometric data as well as joint connections between pelvis and spine on Anderson and Pandy (1999). The planar knee model is described in Yamaguchi and Zajac (1989). The model resembles a specimen of around 75 kg with a body height of roughly 1.80 m. It is suitable for forward dynamic simulations. The original model contains 92 muscle compartments resembling 76 skeletal muscles of the lower extremity and torso. Furthermore, it models 23 degrees of freedom. Our research works using this biomechanical model for the parametric simulation of cycling already show high potential. The resulting activations were of high validity in comparison to empirical EMG measurements. (Miehling and Wartzack, 2014)

To demonstrate the SMA, we reduced this model to the right leg and pelvis as the left side of the body is presumed to be symmetrical. This model contains five degrees of freedom of the hip, knee and ankle (each positive and negative rotation direction) and 43 muscle compartments spanning one or more joints.

3.2 Data Acquisition and Preparation

There are studies available reporting either maximal isometric joint forces/torques or maximum action forces. An action force expresses the maximal force a human being is able to generate in a specific body posture while performing a given task (e.g. load carrying position). Action forces are hard to map onto biomechanical models, because many muscle strength constellations can lead to the same action force. Additionally, the computation of the set of muscle scaling factors based on action forces would be highly complex and computationally intense, since lots of these actions require identical muscles. The underlying postures would have to be considered simultaneously. Not least, these actions typically involve the whole body. For the aim of generating large groups of virtual individuals such approaches do not seem expedient. Notwithstanding, maximum action forces, like for example reported in the German DIN 33441-5 standard (Deutsches Institut für Normung, 1999), are still useful for validation purposes of the adapted biomechanical models.

In contrast, values reported at joint level (forces or torques) can be regarded as nearly context free. These are valid for very isolated body postures just involving adjacent degrees of freedom. Those postures are easier to model and propagation effects are smaller compared to the use of action forces for strength scaling. Even though the musculoskeletal system is highly redundant and additionally several muscles contribute to more than just one joint torque, these relationships are still quantifiable. The relationship between muscles and actuated degrees of freedom can be seen in figure 1 at the example of the musculus biceps femoris. Both heads act as knee flexors. The long head additionally contributes to hip extension. It even supports hip external rotation when the knee is flexed.

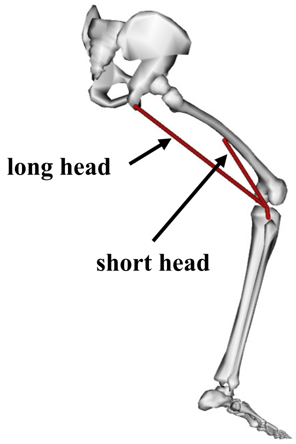

Figure 1. Muscular geometry of both heads of the musculus biceps femoris

There are various studies providing maximum isometric joint forces or torques for a range of age groups and strength percentiles. For example Stoll (2002) measured and percentilised the maximum isometric voluntary joint forces for a healthy population of 20 to 80 years of the Zurich area in Switzerland. The study included almost all larger functional muscle groups of the human body. The only disadvantage of using the data of this publication for strength adaption is the reporting of joint forces instead of joint torques. The application of joint forces presupposes knowledge about the body part dimensions as well as the distribution of the joint forces in relation to the lever arms. Neglecting these relationships, we would risk ignoring the fact that taller persons tend to have higher muscle mass and therefore can generate higher muscle forces.

Strength adaption based on joint torques would automatically take dimensional effects into account. Danneskiold-Samsøe et al. (2009) measured the isokinetic and isometric muscle strength as joint torques in a healthy population ranging from 20 to 80 years. This study was undertaken in the suburban area of Copenhagen. The joint torques are reported as means in line with the related standard deviation for ten year intervals. When average German anthropometric data are assumed to calculate joint torques from the forces reported in Stoll (2002), the findings of the two considered studies are comparable. This indicates that the data is valid for the Central European population.

Before the values reported in Danneskiold-Samsøe et al. (2009) can finally be used to adapt the strength of our generic leg model, it has to be transferred to a computer processible representation. After arranging the population database, the data was smoothed using splines. We chose the smoothing factor in order that the resulting curves were comparable to the curves published by Stoll (2002). Figure 3 shows the smoothing splines for the mean M and standard deviation SD of the maximum hip abduction torque from Danneskiold-Samsøe et al. (2009). Using the resulting curves, normal distributions can be reconstructed for the joint torques. Eventually the target joint torques for a particular age, gender and strength percentile can be computed.

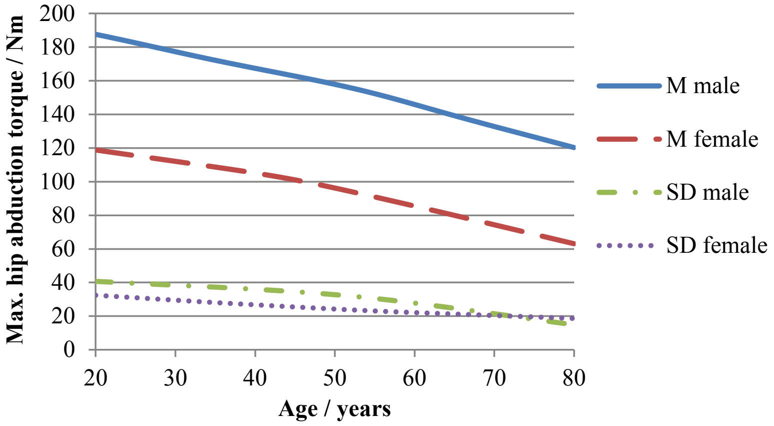

Figure 2. Smoothing splines of maximum hip abduction torque

3.3 The Algorithm

The proposed Strength Mapping Algorithm (SMA) is a computer-based procedure reconstructing the measurement methods applied in the study of Danneskiold-Samsøe et al. (2009) in order to adapt a given generic model to empirical strength data. It is organised in an input, preparation, adaption and evaluation phase. Figure 3 sketches the workflow of the SMA.

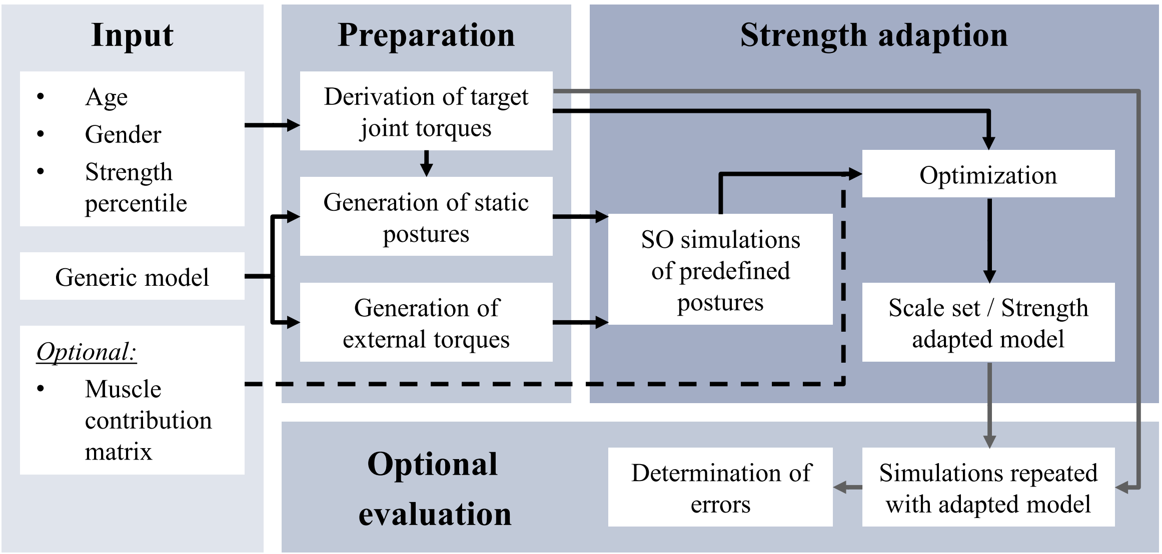

Figure 3. Procedure of the Strength Mapping Algorithm (SMA)

The SMA needs at least some numerical input (age, gender, strength percentile) of the individual to be generated and the generic model specifying the skeletal and muscular geometry as base for the adaption process. In the preparation phase, the target joint torques are calculated for the specified age, gender and strength percentile based on the previously smoothed data. As static optimization (SO) simulations are performed in the adaption process, some more inputs are to be prepared. Static optimization can be seen as an extension to inverse dynamics simulation. It facilitates the computation of individual muscle forces from the net joint torques calculated in inverse dynamics by minimizing a given cost function (e.g. sum of squared muscle activations). To be able to perform a static optimization simulation with a given model, the motion the model should perform as well as the external stress conditions (e.g. forces, torques) acting on the biomechanical model are needed.

In our case the measurement settings of Danneskiold-Samsøe et al. (2009) have to be reconstructed virtually. The torque measurements were performed in isometric condition. In this study, each maximum isometric torque of the lower body was measured in two postures. The higher of the two resulting values was selected as the maximum torque the test person is able to produce at a specific degree of freedom. This leads to a total of 20 load cases to be simulated for our leg model.

For each of the 20 underlying reference poses, we created a time series of the respective joint angle constellations (figure 4). These were used as isometric motions in the static optimization simulations of the subsequent strength adaption phase. During each simulation, the model has to counteract the applied external torque by appropriately activating its muscles. In other words, the joint torques produced by the model have to neutralise or counteract the externally applied torque so that it can stay in the given isometric posture. To be able to assess the torque generating abilities of the model, we created a ramp profile with increasing external torque for each load case. Thereby, the final value of the external torque has to exceed the maximum joint torque which the generic model is capable to exert. To fully replicate the real load conditions, we locked the degrees of freedom of the model which were immobile in the empirical torque measurements.

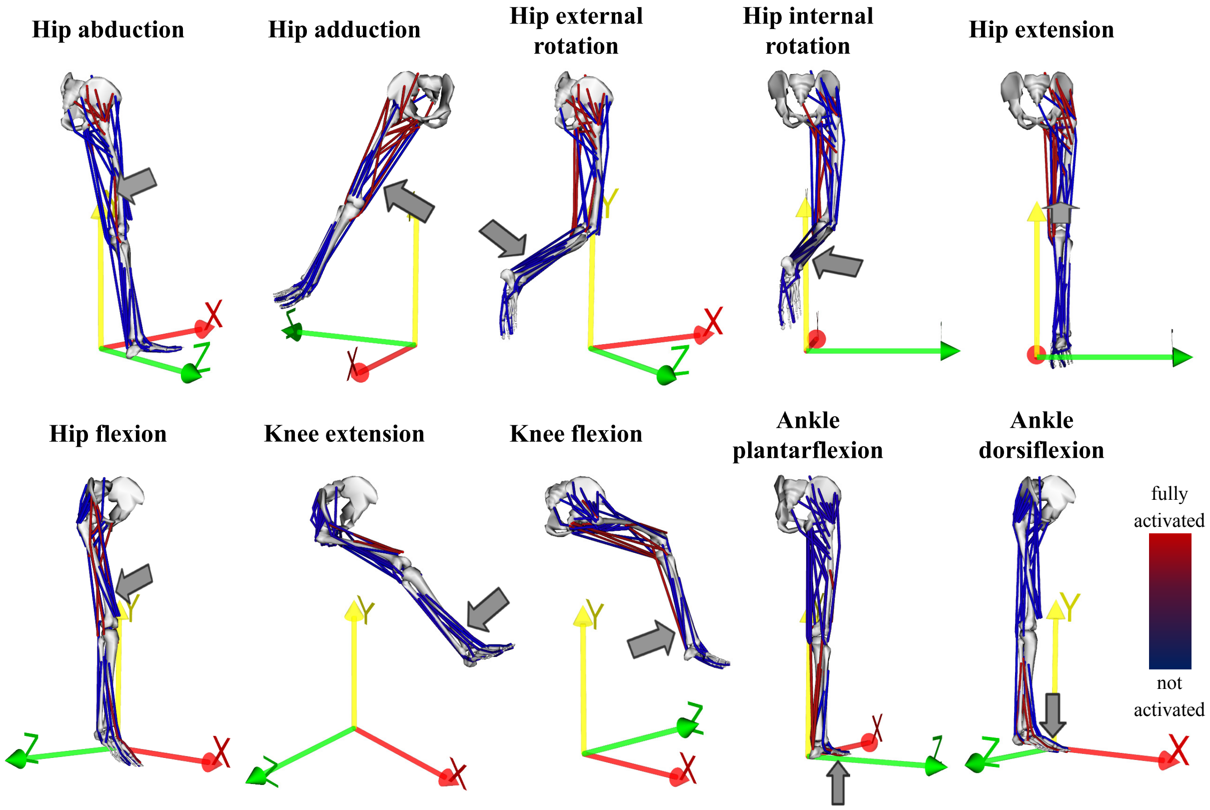

Figure 4. Excerpt of simulated postures at maximum joint torque (arrows: load direction)

After all simulation runs are completed, we evaluate the results to create the muscle contribution matrix, which is needed in the subsequent optimization to determine the set of muscle scaling factors. This matrix contains the information about how much the individual muscles contribute to the maximum joint torques of the generic model. To be able to construct this matrix, the next step is to determine the maximum joint torques the generic model is able to produce. As already mentioned, the externally applied torque is driven up in each simulation, in order that anytime the model cannot sustain the given reference pose by its own strength. At this stage, the mainly deployed muscles are fully activated and the so called reserve actuators start to support the muscles by producing additional torque. This point in the simulation marks the maximum joint torque of the model for the investigated degree of freedom and rotational direction in the given reference pose. Figure 5 shows this relationship for the knee extension torque of the generic leg model.

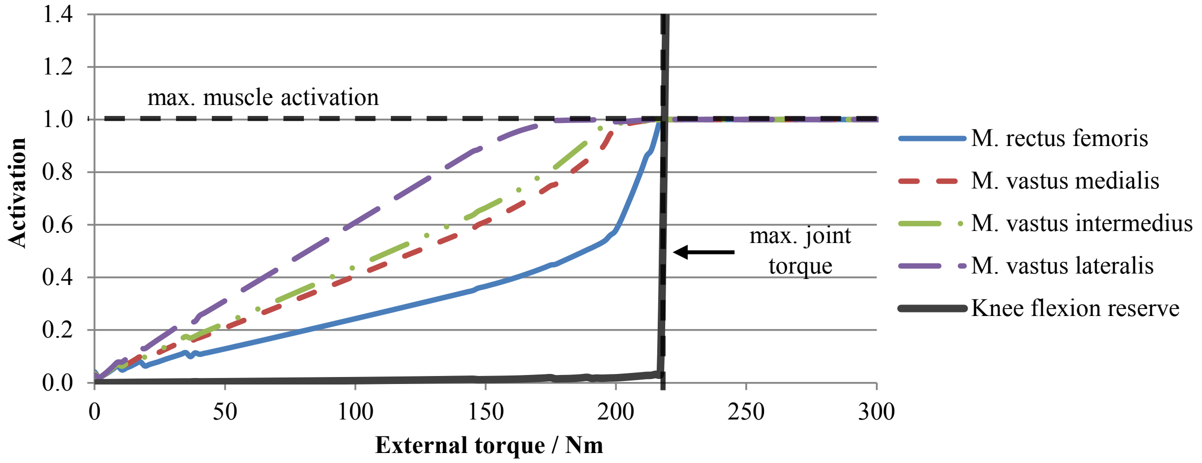

Figure 5. Identification of joint torque maximum for knee flexion

We repeat this procedure to identify the maximum joint torque for all simulated measurement settings of the leg model. Like in the underlying study, the higher result of the two related simulations is taken as maximum isometric torque for the given degree of freedom and torque direction. As soon as all torque maxima are known, a muscle force matrix as well as a muscle lever arm matrix can be constructed. The muscle force matrix contains the individual muscle forces the model exerts to produce the maximum possible joint torques. The muscle lever arm matrix consists of the effective lever arms of all muscles with respect to the rotational axes of all degrees of freedom. Thereby, we consider only positive values, as muscles can only generate pulling and no pushing forces. The muscle contribution matrix is ultimately produced by element-wise multiplication of the muscle force and lever arm matrices. The resulting matrix provides the maximum torques each muscle can generate at every degree of freedom in each torque direction.

A special feature of the SMA is, that the static optimization simulations have to be done only once for a given generic model. As soon as the muscle contribution matrix is known, this most computationally intense part of the SMA can be bypassed and large numbers of demographically adjusted models can be created with just very short time demand.

After we know the contribution of each muscle in the joint torque generating abilities of the generic model as well as the target joint torques for a given individual to be replicated virtually, we can calculate a set of scaling factors in order to adapt the maximum isometric muscle forces of the generic model. The optimization problem for the calculation of the scale set s can be formulated as:

$$\mathrm{s} = \underset{s\in\mathbb{R}^{+}}{\arg\min}\left(\left\|t_{target} - M_{generic}\cdot s\right\| + \{\max(s) - \min(s)\}\right) \tag{2}$$

By solving this optimization problem, the joint torques produced by the individual muscles in the muscle contribution matrix of the generic model $\mathrm{M}_{\mathrm{generic}}$ are scaled in order to reduce the deviation of the resulting maximum joint torques to the target torques $\mathrm{t}_{\mathrm{target}}$. In addition, we reduce the difference of the highest to the lowest scaling factor so that the adapted model stays as close to the muscle force distribution of the generic model as possible. The scaling factors can only be positive real numbers as muscles cannot produce compressive forces. The resulting set of scaling factors is ultimately used to scale the individual maximum isometric muscle force values of the generic input model leading to the demographically adapted biomechanical model. Scaling is done by multiplying each maximum isometric muscle force of the generic model with the corresponding scaling factor.

After an adapted model is generated, an optional evaluation can be conducted to compare the resulting maximum joint torques of the newly created model to the target torques for the given person.

Therefore, the maxima of the external torques applied in the corresponding reference poses are altered to 1.2 times of the target joint torques. Afterwards, the static optimization simulations are repeated with the adapted model in conjunction with the modified external stress levels and unchanged static motions. Then, we determine the resulting deviations of the maximum joint torques to the target torques. Although, the evaluation step is also computationally intense, it is superfluous as long as the behaviour of the generic model in the SMA is known. Otherwise, if an unknown generic model is adapted, this step has to be performed just for a few random samples of the generated virtual user group or population to gain insights about the adapted models' quality.

3.4 Generation of Exemplary Individuals

For evaluation of the SMA's performance, we created four exemplary individuals from the aforementioned generic leg model. The maximum joint torques of the generic model as well as the target joint torques of the four individuals are shown in figure 6.

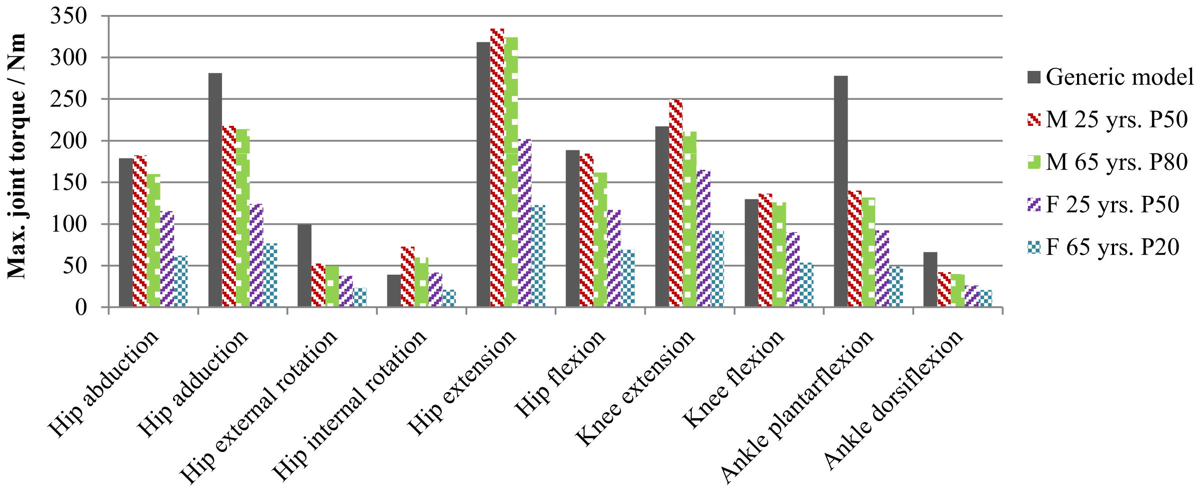

Figure 6. Comparison of maximum joint torque distribution of the generic model to the target joint torques of four exemplary individuals

After the generic leg model was scaled to resemble the target joint torques of the individuals using the stated SMA, we applied the optional evaluation process to reveal the deviations of the maximum joint torques of the adapted models to the target joint torques. For all four demographically adapted leg models we found virtually no errors, the largest deviation being $6.3 \cdot 10^{-4}\,\%\,(1.3 \cdot 10^{-5}\,\mathrm{Nm})$. Thereby, the largest scaling factor was around 2.10 for the strongest individual (M 25 yrs. P50), the lowest approximately 0.09 for the weakest person (F 65 yrs. P20). The mean value of the scaling factors amounted to 1.00 (M 25 yrs. P50), 0.89 (M 65 yrs. P80), 0.63 (F 25 yrs. P50) and 0.36 (F 65 yrs. P20). These values give an impression about the relative strength of the considered individuals.

The present results show that the SMA can be successfully used to create demographically models which accurately match empirical strength data based on the applied leg model.

4 CONCLUSION AND OUTLOOK

In the present paper the Strength Mapping Algorithm (SMA) was shown, extending available methods which are used to adapt other modelling domains like for example anthropometry. The proposed workflow facilitates the adaption of individual maximum isometric muscle forces to match empirical strength data retrieved from literature. This procedure involves static optimization simulations of predefined body poses to reveal the dependencies between muscle forces and joint torques of a generic model specifying the skeletal and muscular geometry. Based on this information, we determine a set of muscle scaling factors for a given age, gender and strength percentile. In this contribution we adapted a generic leg model to different exemplary individuals and evaluated the resulting model against the input data. The results underline, that the SMA enables the quick generation of a large number of demographically correct biomechanical models of the Central European population in a short period of time. If the age and gender distribution (population pyramid) is taken into account valid virtual populations or user groups can be sampled, which in turn can be used to simulate and optimise human-product interactions for specific individuals or user groups. Thereby, the question arises which sample size is necessary to implement a design for populations paradigm in virtual human factors engineering. The resulting virtual populations can additionally be validated considering published action forces for the given population. Further work has to be done to extend the workflow to a full body model. The used dataset also supplies empirical strength data for the major degrees of freedom of the upper body.

REFERENCES

Anderson, F.C. and Pandy, M.G. (1999) A dynamic optimization solution for vertical jumping in three dimensions. Computer Methods in Biomechanics and Biomedical Engineering, Vol. 2, No. 3, pp. 201-231.

Bubb, H., Fritzsche, F. (2009) A Scientific Perspective of Digital Human Models: Past, Present, and Future. In: Duffy, V.G. (ed), Handbook of Digital Human Modeling. Research for Applied Ergonomics and Human Factors Engineering, Boca Raton: CRC Press, pp. 1-26.

Chapanis, A. (1995) Ergonomics in product development: a personal view. Ergonomics, Vol. 38, No. 8, pp. 1625-1638.

Danneskiold-Samsøe, B., Bartels, E.M., Bülow, P.M., Lund, H., Stockmarr, A., Holm, C.C., Wätjen, I., Appleyard, M. and Bliddal, H. (2009) Isokinetic and isometric muscle strength in a healthy population with special reference to age and gender. Acta Physiologica, Vol. 197, Suppl. 673, pp. 1-68.

Delp, S.L., Anderson, F.C., Arnold, A.S., Loan, P., Habib, A., John, C.T., Guendelman, E. and Thelen, D.G. (2007) OpenSim: Open-source Software to Create and Analyze Dynamic Simulations of Movement. IEEE Transactions on Biomedical Engineering, Vol. 54, No. 11, pp. 1940-1950.

Delp, S.L., Loan, J.P., Hoy, M.G., Zajac, F.E., Topp E.L. and Rosen, J.M. (1990) An interactive graphics-based model of the lower extremity to study orthopaedic surgical procedures. IEEE Transactions on Biomedical Engineering, Vol. 37, pp. 757-767.

Deutsches Institut für Normung (1999) DIN 33441-5 Physical strength of man - Part 5: Maximal isometric action forces, values. Berlin: Beuth Verlag.

Fox, M.D., Reinbolt, J.A., Õunpuu, S. and Delp, S.L. (2009) Mechanisms of improved knee flexion after rectus femoris transfer surgery. Journal of Biomechanics, Vol. 42, No. 5, pp. 614-619.

Gilmore, J.H. and Pine, B.J. (2000) Markets of One: Creating customer-unique value through mass customization. Boston: Harvard Business Press.

Hemmelmann, C., Brose, S., Vens, M., Hebebrand, J. and Ziegler, A. (2010) Percentiles of body mass index of 18-80-year-old German adults based on data from the Second National Nutrition Survey. Deutsche Medizinische Wochenschrift (1946), Vol. 135, No. 17, pp. 848-852.

Keys, A., Fidanza, F., Karvonen, M.J., Kimura, N. and Taylor, H.L. (1972) Indices of relative weight and obesity. Journal of chronic diseases, Vol. 25, No. 6, pp. 329-343.

Krüger, D., Miehling, J. and Wartzack, S. (2014) A transdisciplinary approach to model user-product interaction: how the collaboration between human sciences and engineering design could improve product development for physically impaired people. In: Blessing, L., Qureshi, A.J., Gericke, K. (eds), The Future of Transdisciplinary Design, Berlin: Springer.

Max Rubner-Institut (2008) Nationale Verzehrsstudie II. Ergebnisbericht, Teil 1. Die bundesweite Befragung zur Ernährung von Jugendlichen und Erwachsenen, Berlin.

Miehling, J., Geißler, B. and Wartzack, S. (2013a) Towards Biomechanical Digital Human Modeling of Elderly People for Simulations in Virtual Product Development. Human Factors and Ergonomics Society International Annual Meeting 2013, San Diego, Thousand Oaks: Sage, pp. 813-817.

Miehling, J., Krüger, D. and Wartzack, S. (2013b) Simulation in human-centered design – past, present and tomorrow. In: Abramovici, M, Stark, R. (eds), Smart Product Engineering, Berlin: Springer, pp. 643-652.

Miehling, J. and Wartzack, S. (2014) Parametrische biomechanische Simulation am Beispiel des Radfahrens. 25. Symposium Design for X, Bamberg, Hamburg: TuTech Verlag, pp. 273 - 284.

Rasmussen, J., Dahlquist, J., Damsgaard, M., de Zee, M. and Christensen, S.T. (2003) Musculoskeletal modeling as an ergonomic design method. International Ergonomics Association XVth Triennial Conference, Seoul.

Rohmert, W. (1984) Das Belastungs-Beanspruchungs-Konzept. Zeitschrift für Arbeitswissenschaft, Vol. 38, No. 4, pp. 193-200.

Schlick, C., Bruder, R. and Luczak, H. (2010) Arbeitswissenschaft, 3. Edition, Berlin: Springer.

Stoll, T. (2002). Isometric muscle strength measurement. Stuttgart: Thieme.

Story, M., Mueller, J. and Mace, R. (1998) The Universal Design File: Designing for people of all ages and abilities. Design Research and Methods Journal, Vol. 1, No. 1.

Yamaguchi, G.T. and Zajac, F.E. (1989) A planar model of the knee joint to characterize the knee extensor mechanism. Journal of Biomechanics, Vol. 22, No. 1, pp. 1-10.