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COMPUTER MODELING AND SIMULATION OF HUMAN MOVEMENT

Applications in Sport and Rehabilitation

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Computer modeling and simulation of human movement is playing an increasing role in sport and rehabilitation. Two of the more prominent applications in sport include optimizing technique[1, 3, 32, 51, 85] and designing equipment to improve performance.[4, 20, 34, 71, 79] Sport technique is a motor skill that is learned and often requires complex muscle coordination patterns. The complexity stems from the ability of muscles to accelerate joints and segments they do not span, and is complicated further by biarticular muscles that can accelerate joints in opposite directions from their anatomic classification.[83] Understanding the interactions within the complex musculoskeletal system and the causal relationships between these interactions is necessary to effectively optimize sport technique. Modeling and simulation allows for the systematic examination of specific parameters (e.g., equipment) on performance without the confounding effect of adaptation[21] and identification of those parameters most influential on performance.

Applications of modeling and simulation in rehabilitation include examining injury mechanisms,[28, 47] joint loading,[13, 45, 75] functional electrical stimulation,[14, 27, 54, 78] surgical planning techniques,[18, 56] muscle function,[37, 46, 53, 55] and normal and pathologic gait.[16, 30, 57, 65] Muscle coordination can be altered within limits during a given movement task to help reduce musculoskeletal loading. But it is not clear a priori how these

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changes affect the loading because of the highly nonlinear dynamics and complex interactions between the musculoskeletal system and the environment. Changes in the movement caused by altered muscle coordination result in changes in the muscle kinematics, and therefore in the muscle and ground reaction forces. These circular dynamic interactions within the musculoskeletal system make these responses difficult to predict and interpret, and the effects are often counterintuitive. Experimental data and analytical techniques based on inverse dynamics are not sufficient to identify these interactions between system inputs (e.g., technique, equipment) and outputs (e.g., task performance, joint loading).[82]

Forward dynamics simulations can identify how individual muscles contribute to task performance, which is the foundation for understanding and treating pathological gait, designing functional electrical stimulation strategies, and providing valuable information for surgical planning. These examples highlight some of the many applications of forward dynamics simulation in the fields of sport and rehabilitation. The purpose of this article is to provide an overview of the forward dynamics simulation approach and present an example application in the field of rehabilitation.

FORWARD DYNAMICS SIMULATIONS

The forward dynamics approach uses a mathematical model that is analogous to how the human neuromuscular system functions to perform a given motor task. A neuromuscular control signal is sent to the muscles to generate a force that is applied to the body segments, and a movement trajectory results (Fig. 1). The movement trajectory is dependent on the system dynamics and the time history of the muscle forces, unlike the inverse dynamics approach which cannot identify how the muscle forces affect the movement of the segments and joints. The forward dynamics approach provides a direct mapping between the control inputs and the resulting movement trajectories that allow for the identification of causal relationships between various neuromuscular and biomechanical parameters and the task performance. Because the forward dynamics approach includes the system dynamics, there is assurance that the results are consistent with the dynamic properties of the musculoskeletal system. In addition, the forward dynamics approach includes a biomechanical model of the system that allows the joint reaction forces to be determined during different movement tasks and coordination strategies.

Forward dynamics simulations consist of a biomechanical model of the musculoskeletal system, joint moment or muscle force actuators, neuromuscular control model, and a framework to identify the control patterns necessary to produce realistic well-coordinated movements. Each of these components is discussed in detail later. Once the model is

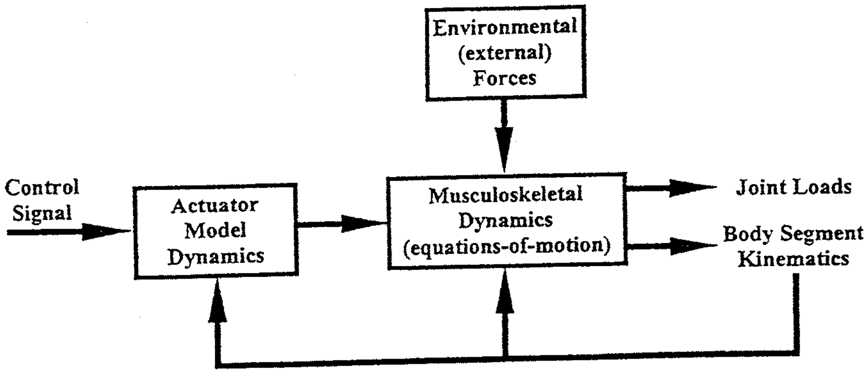

Figure 1. Forward dynamics representation of the musculoskeletal system. The nervous system generates a movement by sending a control signal to produce an actuator force. The force interacts with the external forces applied to the musculoskeletal system to produce corresponding body segment kinematics (i.e., segment orientations, velocities, and accelerations). These kinematics determine the state of the system that, in turn, affects the actuator and musculoskeletal dynamics.

formulated and a simulation is produced, two important steps are the validation of the model and the interpretation of the results.

Musculoskeletal Model

The musculoskeletal system is most commonly modeled as a rigid-segment, multilink system with articulating joints. Such biomechanical models can be studied analytically by deriving the equations of motion that describe how the motion of the system varies when forces are applied to the system (e.g., muscle forces), and how it interacts with the environment. For simple systems with few degrees of freedom, the equations of motion can be derived using standard Newton-Euler, Lagrange, or Kane's equations. But for more complex multibody systems, automated derivations are possible through commercial packages (e.g. Symbolic Dynamics, Inc., Mountain View, CA; DADS, CADSI, Coralville, IA).

Biomechanical models represent a complex musculoskeletal system, and therefore, care must be taken to ensure that the model formulation is detailed enough to address the questions of interest. Simple models may omit important system characteristics and provide false insights. For example, modeling the knee joint flexion/extension kinematics with a purely revolute joint may provide inaccurate estimates of the knee joint moment arms, and therefore the joint moments, because the instantaneous center of rotation translates with knee flexion.[48, 77] But overly complex models can generate too many independent variables, making interpretation of the results difficult. The number and type of segments, dimensionality, and types of joints should be considered carefully. For example, some degrees of freedom may not contribute to the motion of interest (e.g., frontal plane motion in cycling) and may be disregarded. Models should be simple enough to capture the essential behavior of the system for the questions of interest, and complexity should only be added when the model does not capture this behavior. Simple models can provide important insight into a variety of biomechanical problems.[5, 49] Commercial software packages with graphic user-interfaces are available to help develop musculoskeletal models and visualize the results of simulations (e.g., SIMM, MusculoGraphics, Inc., Evanston, IL; DADS, CADSI, Coralville, IA).

An important aspect of the model development is the parameter identification. Musculoskeletal anthropometrics, segment inertial characteristics, and passive structural properties all need to be estimated and can provide a large source of error.[8, 10] Many of these parameters are based on cadaver measurements and generalized to the normal population. But recent developments in methods to identify subject specific model parameters using imaging techniques have the potential to greatly improve musculoskeletal models (see below).

Actuator Model

Simulations of human movement usually are driven by either joint moment[24, 36] or individual muscle[44, 55] actuators. Joint moment actuated simulations have the advantage that the muscle origin and insertion points, lines of action, and muscle specific parameters (e.g., maximum isometric force, tendon and fiber rest lengths, pennation angles) do not need to be specified. But these simulations have similar limitations as the inverse dynamics approach when attempting to address questions related to muscle function and coordination. The joint moment trajectories do not provide individual muscle contributions to the task performance, and the joint moment values can be unrealistic because they do not consider the force-length-velocity relationships of skeletal muscle. Further, co-contraction between antagonistic muscles and the effect of biarticular muscles between joints cannot be identified. The remainder of the article is limited to simulations driven by individual muscle actuators.

Muscle Actuators

There are two important components to consider when modeling muscle force actuators: the activation dynamics and musculotendon contraction dynamics (Fig. 2). The muscle activation dynamics (or excitation-contraction coupling) usually is represented by a first-order differential equation that converts the neural excitation into muscular activation.[82] The model for the musculotendon contraction dynamics is almost

Figure 2. Musculotendin actuator dynamics. Neural excitation is low pass filtered to produce muscle activation. Process models time course of chemical reactions during muscle force development.

exclusively modeled as a lumped parameter Hill-type model in human movement analyses.[73, 82] Although more sophisticated models have been developed to describe the biophysical contraction mechanisms,[31, 80] Hill-type muscle models are computationally efficient, perform well during a variety of movement and contractile conditions, and are sufficient to understand muscle function in dynamic movement simulations.[6, 73, 74]

The Hill-type muscle model consists of three elements: a contractile element, series elastic element, and parallel elastic element. The force generated in the contractile element is governed by the force-length and force-velocity properties of skeletal muscle. Implicit with this model are the assumptions that all muscle fiber sarcomeres are homogeneous, muscle fibers are parallel and insert into the muscle tendon at the same orientation, and muscle volume and physiologic cross-sectional area (PCSA) are constant throughout the muscle. Most muscle models do not consider individual fiber types or history effects such as fatigue, stretch-shortening, and force depression.

Determining the Neuromuscular Control

One of the most difficult and important components of generating a forward dynamics simulation is finding neuromuscular controls that produce well-coordinated movements. The two primary methods used to find the controls either seek to replicate experimentally measured data or optimize a performance based objective function. These methods generate a set of open-loop controls that are usually specified as a function of time or position without any feedback (e.g., reflex responses, sensory afferent signals) during the movement. The feedback is considered to have occurred already and the control signal is the summation of the central and feedback commands.

The first method that seeks to replicate experimental data is known as the tracking solution. The method manipulates the control variables to minimize the difference between the simulation and experimental data in a least mean-square sense. The tracking solution is useful for producing a baseline simulation to test movement control hypotheses, identify joint loading and injury mechanisms, quantify muscle contributions to task performance, and perform sensitivity analyses.[15, 27, 43, 46, 75]

The challenge in solving the tracking solution is identifying which quantities to include in the objective function because different formulations can provide different solutions.[44]

The second method used to find the muscle controls optimizes a mathematically defined performance based objective function. In this case, the goal of the simulation needs to be clearly defined. Previous examples include maximum height jumping,[3, 51] maximum speed pedaling,[55, 60] maximum power,[4, 79] minimum rate of acceleration,[22] and minimum torque change.[67] These studies have clearly defined goals that seek to minimize or maximize some quantity that defines the task performance. But many questions in sport and rehabilitation occur at the submaximal level when the objective function is not clearly defined and many neuromuscular and biomechanical factors can influence the control strategy.[84] In these situations, simulation provides a powerful tool for investigating specific factors hypothesized to govern movement control, such as metabolic energy expenditure or muscle fatigue.[35, 43] If a proposed factor formulated as an objective function produces a well-coordinated movement, then confidence in that control principle is gained.

Another method is to combine the tracking solution with a performance-based criterion.[15] Although this method appears promising, it introduces additional complexities that require appropriate weighting in the cost function between the tracking error and the performance quantity. Identifying appropriate weighting is difficult because little is known about what criteria the nervous system uses to select coordination strategies.

Open-loop controls, like those obtained previously, are appropriate in many movements where stability is not a concern, steady-state trajectories are easily obtained (e.g., pedaling), or the questions of interest are not related to movement control. But when stability, system response, or movement control questions are of interest, feedback to the control system is necessary. This type of feedback, or closed-loop control, emulates the human neuromuscular system that continually modifies the motor patterns through sensory feedback.[52, 68] Simulations with feedback control have been able to successfully adapt to movement perturbations, obstacles, and changes in the environment, and provide an increased understanding of movement control.[27, 30, 64, 69]

Once the objective function is formulated using either a tracking or performance based criterion, an optimization algorithm is needed to find the muscle control patterns that minimize or maximize the objective function. Most often, the optimal control problem, where the controls are defined as functions of time, is converted to a parameter optimization where the controls are discretized and solved with readily available algorithms.[50] The conceptual framework for performing a parameter optimization with a forward dynamics simulation is presented in Figure 3. The optimization starts with an initial guess for the control parameters which normally are guided by experimental data or intuition. A simulation is performed with the initial guess and the appropriate data are extracted from the simulation to be used in the objective function. The

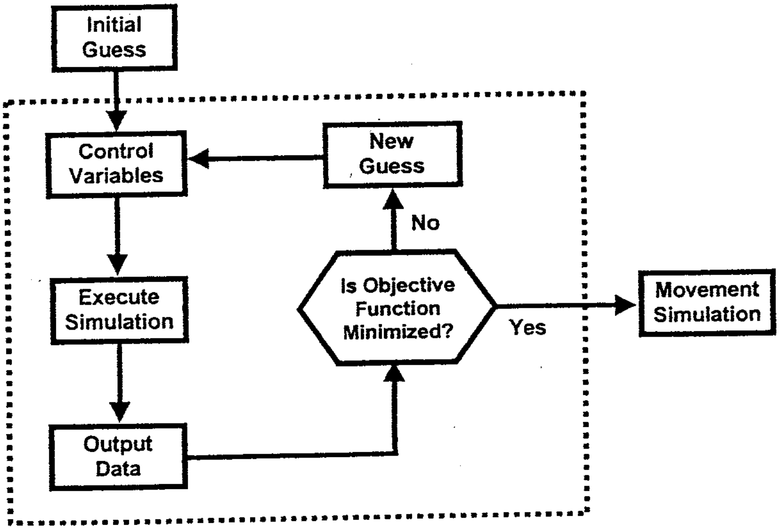

Figure 3. Forward dynamics optimization framework. Dotted line = optimization algorithm.

objective function then is computed and evaluated to see if it has been optimized based on user defined criteria. If the simulation meets the criteria, then the optimization is stopped. If the simulation does not meet the criteria, then the control parameters are manipulated and another iteration is performed.

Because of the highly coupled, dynamic nature of the musculoskeletal system, the objective function is usually highly nonlinear, and solutions with conventional gradient algorithms are difficult to achieve.[42] But global optimization algorithms, increased computer speeds, and parallel computer architectures have led to improved computational performance and convergence.[2, 9, 42] In addition, the solution space can be reduced by assuming bilateral control symmetry between limbs and applying constraints on the control patterns governed by experimental data.

Model and Simulation Validation

An important step in modeling and simulation is validating the model to assure it is producing realistic results. One form of validation is to compare the simulation results with experimentally measured data. This type of validation can be difficult because the model often is developed because similar experiments cannot be performed on human subjects. Further, comparison with kinetic and kinematic data alone is not sufficient to validate the model because the redundancy in the neuromuscular system can generate similar kinetic and kinematic patterns with different muscle coordination strategies. Another form of validation is a sensitivity analysis on the model parameters. If the results are highly sensitive to a specific parameter, then care should be taken in selecting that parameter. The final form of validation is achieved through perturbation tests. For example, Wright et al[76] developed a simulation model to examine the sensitivity of ankle sprain occurrence to muscle strength and initial conditions. They compared the model's response to small perturbations in the floor surface orientation with the response of human subjects to those same perturbations. They found that the responses were similar, and therefore gained confidence in their model to investigate ankle sprains.

EXAMPLE APPLICATION OF SIMULATION IN REHABILITATION

A validated model and simulation provides a rich environment to address many questions in the fields of sport and rehabilitation. Many studies can be performed with the model that cannot be performed with human subjects, such as identifying injury mechanisms, optimal technique and equipment to improve performance, and the influence of muscle coordination patterns on joint loading. One such example is taken from a recent study investigating the sensitivity of knee joint loading to pedaling direction.[45] This question has important implications for those patients using pedaling as a rehabilitation exercise to recover from a knee injury.

Pedaling a stationary ergometer is an important component of many lower extremity rehabilitation programs for pathologies such as patellofemoral pain. Forward pedaling has been used to rehabilitate patellofemoral pain because it can strengthen the quadriceps muscle group while reducing the compressive loading in the patellofemoral joint relative to full weight-bearing exercises. Recently, backward gait has been shown to provide several rehabilitative advantages over forward gait, including greater knee extensor moments[19, 72] and reduced patellofemoral joint loads.[23] These results have provided the basis for prescribing backward gait as a common component of functional knee rehabilitation.[12] The success in backward gait has led others to suggest that backward pedaling might provide similar advantages over conventional forward pedaling.[7] No study has examined the biomechanical differences, however, in patellofemoral joint loading during forward and backward pedaling. The task mechanics of backward pedaling require quadriceps activity during regions of greater knee flexion compared to forward pedaling (Fig. 4).[7, 66] But knee extensor activity during high flexion angles increases patellofemoral loads,[63] and therefore backwards pedaling may not be an effective rehabilitative exercise for patellofemoral pain. The difference in joint loading between forward and backward pedaling has not been examined primarily because measuring the joint loads in vivo is pres-

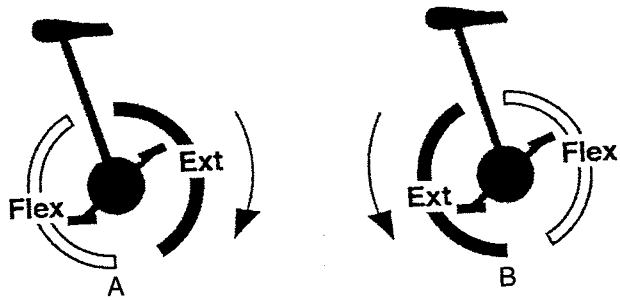

Figure 4. General regions of muscle activity in forward *(A)* versus backward *(B)* pedaling for the extensor (Ext) and flexor (Flex) muscle groups. In backward pedaling the quadriceps muscle group (Ext) is active during crank cycle when the knee is in a more flexed position (see Fig. 7).

ently too difficult. This provides an ideal problem to address using forward dynamics simulations.

To investigate whether backward pedaling offers theoretic advantages over forward pedaling in the rehabilitation of patellofemoral pain, a musculoskeletal model and simulation of forward and backward pedaling was used to quantify the sensitivity of patellofemoral joint loads to pedaling direction.

METHODS

Musculoskeletal Model

As previously described a planar two-legged bicycle-rider musculoskeletal model was used in the analysis (Fig. 5).[44] The model and equations of motion were derived using SIMM (MusculoGraphics, Inc., Evanston, IL) and SD/FAST (Symbolic Dynamics, Inc., Mountain View, CA). Each leg was modeled with three rigid-body segments (thigh, shank, and foot), with the hip joint center fixed and foot rigidly attached to the pedal. The joints were modeled as revolute at the hip and ankle joints, whereas the tibiofemoral joint was modeled with three degrees of freedom with a moving center of rotation for flexion-extension specified as a function of knee flexion angle.[17] The patella served as the insertion point for the quadriceps muscles and was constrained to move along a prescribed trajectory relative to the femur as a function of knee flexion angle.[17] The model was driven by 14 individual Hill-type musculotendon actuators that were combined into nine muscle groups, with muscles within each group receiving the same excitation signal (see Fig. 5). The muscle activation dynamics were modeled by a first-order differential equation.[55]

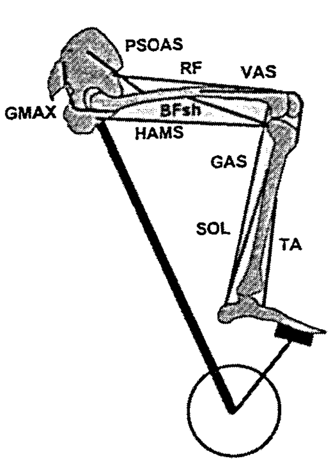

Figure 5. Musculoskeletal model of right leg of the bicycle rider system. Fourteen muscles used in model were combined into muscle groups, with each muscle within its group receiving the same excitation. Muscle groups included: PSOAS = iliacus, psoas; GMAX = gluteus maximus, adductor magnus; VAS = three-component vastus; HAMS = medial hamstrings, biceps femoris long; SOL = soleus; BFsh = biceps femoris short; GAS = gastrocnemius; RF = rectus femoris; TA = tibialis anterior.

Neuromuscular Controls

The individual muscle excitation patterns were considered symmetric and 180° out-of-phase between the left and right legs, and modeled as square waves defined by an onset, offset, and magnitude. The control patterns necessary to produce forward and backward pedaling simulations were determined by finding the tracking solution that minimized the objective function:

$$J = \sum_{j=1}^{m} \sum_{i=1}^{n} \frac{(Y_{ij} - \hat{Y}_{ij})^2}{SD_{ij}^2} \tag{1}$$

where

Y_{ij} = experimentally measured data
$\hat{Y}_{ij}$ = corresponding simulation data
SD_{ij} = intersubject standard deviations
n = number of data points
m = number of variables evaluated

The objective function was formulated to minimize the difference between the simulation and experimental data. The difference was squared to prevent positive and negative differences from canceling each other and normalized by the intersubject variability to give those quantities with lower variability (i.e., more reproducible) more weight in the objective function.

Previously collected experimental data (radial and tangential pedal force components and pedal angle)[66] were used in the objective function. Data were collected during forward and backward pedaling from 16 healthy subjects (8 male, 8 female) at 60 rpm with a frictional workload of 120 J/cycle. A simulated annealing algorithm[29] was used to determine the muscle controls that minimized the objective function and an inequality constraint was enforced to assure the simulations pedaled at the average experimentally measured pedaling plus or minus 2 rpm. To quantify the sensitivity of patellofemoral joint loads to pedaling direction, the total joint reaction force was computed and the peak joint force was quantified.

RESULTS

The optimization algorithm was able to find the muscle controls that produced a simulation that closely matched the group averaged experimental data (Fig. 6) with average pedaling rates of 62 and 60 rpm for the forward and backward directions, respectively. The simulated

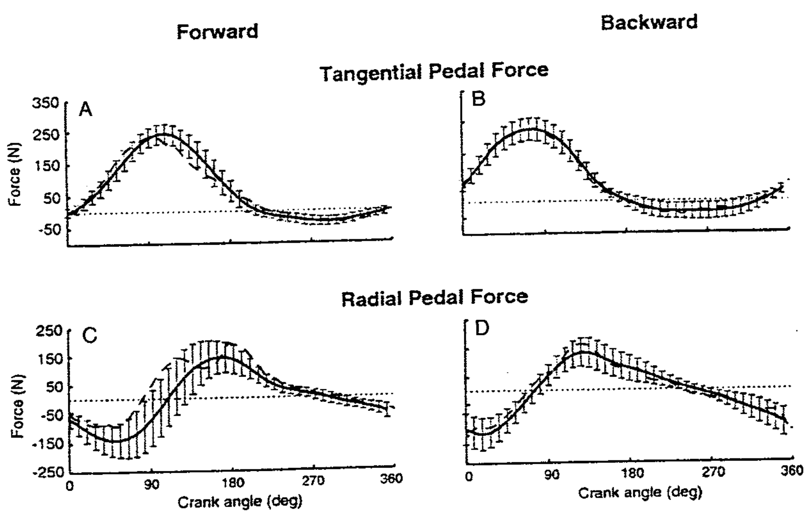

Figure 6. Comparison between simulation and group average experimental pedal force data. Crank angle is positive in direction of pedaling. Crank angle is 0° when crank arm is parallel with seat tube and the limb is in flexed position. *A* and *B*, Positive tangential pedal force accelerates crank. *C* and *D*, Positive radial force is directed towards crank center. Solid line = experimental; dashed line = simulation.

pedal forces and pedal angle in both pedaling directions were almost always within 1 standard deviation (SD) of the experimental data, and there was also close agreement between the muscle excitation and group electromyogram (EMG) data (Fig. 7).

The patellofemoral joint loading patterns were similar in both pedaling directions. But the peak total joint load was 30% greater in backward pedaling compared with forward pedaling (Fig. 8).

DISCUSSION

A forward dynamics simulation approach was used to determine whether backward pedaling offers theoretic advantages over forward pedaling to rehabilitate patients with patellofemoral pain. As with any

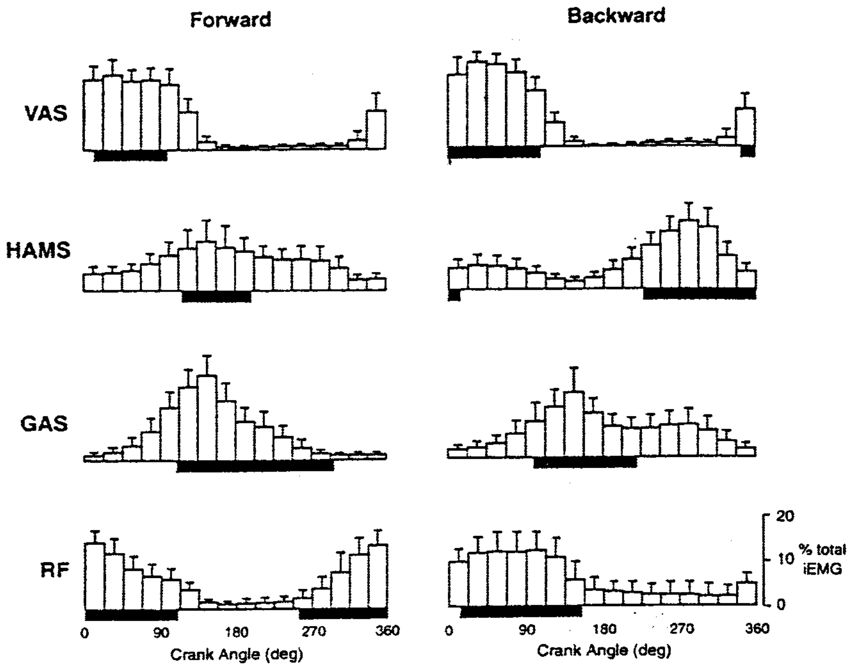

Figure 7. Comparison between simulation and group average experimental muscle excitation data. Solid horizontal bars = simulation onset and offset timing found by tracking solution; vertical bars = experimental EMG data (mean [SD] normalized iEMGs with 16 equally spaced bins) averaged over all subjects; VAS = three-component vastus muscle group; HAMS = medial hamstrings, biceps femoris long muscle group; GAS = gastrocnemius; RF = rectus femoris muscle group.

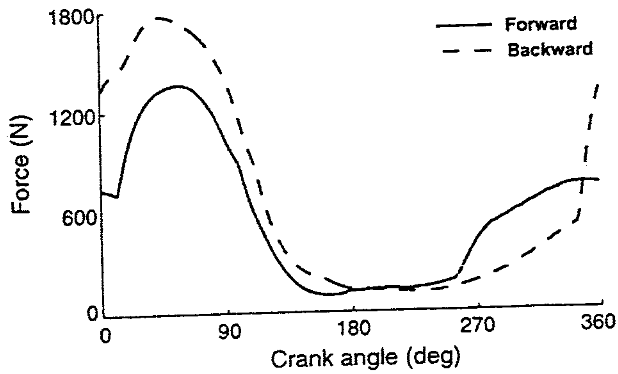

Figure 8. Total patellofemoral joint load. Crank angle is positive in direction of pedaling. Crank angle is 0° when crank arm is parallel with seat tube and limb is in flexed position.

simulation study, results always should be interpreted with the limitations of the model in mind.

A potential limitation of the present study is the mathematical model used to describe the knee joint that has been used in a variety of simulation studies.[44, 53, 55] The sagittal plane model is based on experimental kinematic data and does not include axial rotation of the tibia relative to the femur. Because the present study is focused on the knee joint loads, the implications of using such a model should be considered carefully. Pedaling is primarily a sagittal plane movement with the foot rigidly attached to the pedal. Axial rotation in pedaling is limited primarily to that which naturally occurs during flexion-extension movements, and therefore is kinematically the same in both pedaling directions. Because the kinematics in forward and backward pedaling are similar, the differences in the joint loading because of axial rotation is similar in both pedaling directions, and therefore a qualitative comparison between forward and backward pedaling is unaffected.

An important consideration in studying human movement is the uniqueness of the muscle coordination patterns. Because there are more muscles than degrees of freedom in the model, the simulation muscle coordination pattern that reproduced the experimental data is not unique. There are many coordination patterns that could have produced similar pedaling mechanics, and possibly with lower joint loads than observed. In the present study, the power of the simulation approach is not so much in identifying absolute magnitudes of the joint loading, but insight into the relationship between pedaling mechanics and joint loading.

To assess the sensitivity of the joint loading to the specific muscle coordination patterns used to produce the simulations, a post-hoc sensitivity analysis was performed. Because the knee joint loads are of interest, the magnitudes of the hamstring and vasti muscle excitation were independently varied plus or minus 10%, and the difference in peak joint loading was quantified. The results showed that the difference in peak joint load between forward and backward pedaling averaged 65% and was independent of the excitation magnitude variations. These results suggest that the difference in joint loading between forward and backward pedaling is governed primarily by the pedaling mechanics, not the specific muscle coordination pattern used. These results give confidence in the model to examine differences in patellofemoral joint loading between forward and backward pedaling.

The simulation results showed that greater patellofemoral loads are generated during backward pedaling. The vasti muscles are the primary power producers in backward pedaling and produce peak power when the knee is in a more flexed position than in forward pedaling.[46] These pedaling mechanics produce large compressive loads in the patellofemoral joint (see Fig. 8). The sensitivity analysis of the quadriceps excitation on joint loading showed that the patellofemoral joint load responded fairly linearly with the quadriceps activity, with greater loads always occurring in backward pedaling. These results are consistent with other studies showing increased patellofemoral loads are associated with extensor activity at high flexion angles.[63] Although backward pedaling may be useful in developing an increased extensor moment because of an increase in extensor activity over that in forward pedaling,[7, 66] the results of the present study suggest that forward pedaling, rather than backward pedaling, should be prescribed for those patients with patellofemoral pain.

SUMMARY AND FUTURE DIRECTIONS

The preceding example highlighted one use of forward dynamics simulations by providing insight into pedaling mechanics and joint loading and the implications for prescribing rehabilitative exercises. Forward dynamics simulations emulate how the neuromuscular system functions by mapping a control signal into a movement that assures the resulting movement is consistent with the system dynamics. This characteristic is important when attempting to understand the neural and biomechanical interactions during a movement task to identify control strategies, develop effective rehabilitation programs, or optimize sporting technique and equipment.

Modeling and simulation also provides a powerful educational tool. Scientists and educators can develop neuromusculoskeletal models, generate forward dynamics simulations of a desired motor task, and produce animations of the movement highlighting many of the cause and effect relationships that exist. Increased computer speeds and intuitive modeling and simulation software packages are making the integration of simulation into education easily accessible.

One of the greatest challenges facing the simulation field is the development of musculoskeletal models that include subject-specific anatomic and physiologic parameters, such as joint geometry and muscle properties. Subject-specific models allow scientists and surgeons to make subject-specific recommendations regarding rehabilitation strategies and surgical interventions, as well as provide coaches and biomechanists the insight needed to make recommendations regarding optimal technique and equipment design. Recent studies have demonstrated the feasibility of constructing subject-specific musculoskeletal models by using medical image data to determine muscle moment arms,[39, 41, 58, 62] calculate muscle volumes and limb inertial parameters,[33, 38, 40] estimate muscle physiologic cross-sectional areas,[26, 59] measure muscle pennation angles and fascicle lengths,[25] and describe bone geometry.[11, 61, 70] But these techniques can be computationally intensive, and incorporating the data into subject-specific musculoskeletal models is not trivial. The future looks promising, however, as these techniques are refined and efficient algorithms are developed to generate these subject-specific models.

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References

1. Allinger TL, van den Bogert AJ: Skating technique for the straights, based on the optimization of a simulation model. Med Sci Sports Exerc 29:279–286, 1997
2. Anderson FC, Ziegler JM, Pandy MG, et al: Application of high-performance computing to numerical simulation of human movement. J Biomech Eng 117:155–157, 1995
3. Bobbert MF, Gerritsen KG, Litjens MC, et al: Why is countermovement jump height greater than squat jump height? Med Sci Sports Exerc 28:1402–1412, 1996
4. Bogert AJvd: Optimization of cycling performance using computer simulation. Proceedings of the Second World Congress of Biomechanics. Amsterdam, The Netherlands, 1994, p 135
5. Bogert AJvd, Allinger TL: A Model for determining optimal ski skating techniques. XVIth Congress of the International Society of Biomechanics. Tokyo, Japan, 1997, p 409
6. Bogert AJvd, Gerritsen KG, Cole GK: Human muscle modelling from a user's perspective. J Electromyogr Kinesiol 8:119–124, 1998
7. Bressel E, Heise GD, Bachman G: A neuromuscular and metabolic comparison between forward and reverse pedaling. Journal of Applied Biomechanics 14:409, 1998
8. Cappozzo A, Berme N: Biomechanics of Human Movement: Applications in Rehabilitation, Sport and Ergonomics. Worthington, OH, Bertec Corp, 1990, pp 179–185
9. Casius LJR, Soest AJv: Parallel genetic algorithms for optimization in musculoskeletal modeling. VIIth International Symposium on Computer Simulation in Biomechanics. Calgary, Canada, 1999, pp 36-40
10. Challis JH: Accuracy of human limb moment of inertia estimations and their influence on resultant joint moments. J Appl Biomech 12:517–530, 1996
11. Chao EY, Lynch JD, Vanderploeg MJ: Simulation and animation of musculoskeletal joint system. J Biomech Eng 115:562–568, 1993
12. Clarkson E, et al: Oxygen consumption, heart rate, and rating of perceived exertion in young adult women during backward walking at different speeds. J Orthop Sports Phys Ther 25:113–118, 1997

13. Cole GK, Nigg BM, van den Bogert AJ, et al: Lower extremity joint loading during impact in running. Clinical Biomechanics 11:181–193, 1996
14. Dariush B, Parnianpour M, Hermami H: Stability and a control strategy of a multilink musculoskeletal model with applications in FES. IEEE Trans Biomed Eng 45:3–14, 1998
15. Davy DT, Audu ML: A dynamic optimization technique for predicting muscle forces in the swing phase of gait. J Biomech 20:187–201, 1987
16. Delp SL, Arnold AS, Speers RA, et al: Hamstrings and psoas lengths during normal and crouch gait: Implications for muscle-tendon surgery. J Orthop Res 14:144–151, 1996
17. Delp SL, et al: An interactive graphics-based model of the lower extremity to study orthopaedic surgical procedures. IEEE Trans Biomed Eng 37:757–767, 1990
18. Delp SL, Statler K, Carroll NC: Preserving plantar flexion strength after surgical treatment for contracture of the triceps surae: A computer simulation study. J Orthop Res 13:96–104, 1995
19. DeVita P, Stribling J: Lower extremity joint kinetics and energetics during backward running. Med Sci Sports Exerc 23:602–610, 1991
20. Ekevad M, Lundberg B: Simulation of 'smart' pole vaulting. J Biomech 28:1079–1090, 1995
21. Ferris DP, Liang KL, Farley CT: Runners adjust leg stiffness for their first step on a new running surface. J Biomech 32:787–794, 1999
22. Flash T, Hogan N: The coordination of arm movements: An experimentally confirmed mathematical model. J Neurosci 5:1688–1703, 1985
23. Flynn TW, Soutas-Little RW: Patellofemoral joint compressive forces in forward and backward running. J Orthop Sports Phys Ther 21:277–282, 1995
24. Fregly BJ, Zajac FE: A state-space analysis of mechanical energy generation, absorption, and transfer during pedaling. J Biomech 29:81–90, 1996
25. Fukunaga T, Kawakami Y, Kuno S, et al: Muscle architecture and function in humans. J Biomech 30:457–463, 1997
26. Fukunaga T, et al: Physiological cross-sectional area of human leg muscles based on magnetic resonance imaging. J Orthop Res 10:928–934, 1992
27. Gerritsen KGM: Computer simulation of FES-assisted locomotion. Department of Medical Science, University of Calgary, 1997, pp 1–116
28. Gerritsen KG, Nachbauer W, van den Bogert AJ: Computer simulation of landing movement in downhill skiing: Anterior cruciate ligament injuries. J Biomech 29:845–854, 1996
29. Goffe WL, Ferrier GD, Rogers J: Global optimization of statistical functions with simulated annealing. Journal of Econometrics 60:65–99, 1994
30. Hase K, Yamazaki N: Computer simulation of the ontogeny of bipedal walking. Anthropological Science 106:327–347, 1998
31. Hatze H: A general myocybernetic control model of skeletal muscle. Biol Cybern 28:143–157, 1978
32. Hubbard M: Optimal javelin trajectories. J Biomech 17:777–787, 1984
33. Jaegers SM, Arendzen JH, de Jongh HJ: Changes in hip muscles after above-knee amputation. Clin Orthop 319:276–284, 1995
34. Kautz SA, Hull ML: Dynamic optimization analysis for equipment setup problems in endurance cycling. J Biomech 28:1391–1401, 1995
35. Kautz SA, Neptune RR, Zajac FE: General coordination principles elucidated by forward dynamics: Minimum fatigue does not explain muscle excitation in dynamic tasks. Motor Control 4:101–106, 2000
36. Kepple TM, Siegel KL, Stanhope SJ: Relative contributions of the lower extremity joint moments to forward progression and support during stance. Gait and Posture 6:1–8, 1997
37. Kuo AD, Zajac FE: Human standing posture: Multi-joint movement strategies based on biomechanical constraints. Prog Brain Res 97:349–358, 1993
38. Martin PE, Mungiole M, Marzke MW, et al: The use of magnetic resonance imaging for measuring segment inertial properties. J Biomech 22:367–376, 1989
39. McGill SM, Patt N, Norman RW: Measurement of the trunk musculature of active males using CT scan radiography: Implications for force and moment generating capacity about the L4/L5 joint. J Biomech 21:329–341, 1988

40. Mungiole M, Martin PE: Estimating segment inertial properties: Comparison of magnetic resonance imaging with existing methods. J Biomech 23:1039–1046, 1990
41. Nemeth G, Ohlsen H: In vivo moment arm lengths for hip extensor muscles at different angles of hip flexion. J Biomech 18:129–140, 1985
42. Neptune RR: Optimization algorithm performance in determining optimal controls in human movement analyses. J Biomech Eng 121:249–252, 1999
43. Neptune RR, Hull ML: A theoretical analysis of preferred pedaling rate selection in endurance cycling. J Biomech 32:409–415, 1999
44. Neptune RR, Hull ML: Evaluation of performance criteria for simulation of submaximal steady-state cycling using a forward dynamic model. J Biomech Eng 120:334–341, 1998
45. Neptune RR, Kautz SA: Knee joint loading in forward versus backward pedaling: Implications for rehabilitation strategies. Clin Biomech, 2000, in press
46. Neptune RR, Kautz SA, Zajac FE: Muscle contributions to specific biomechanical functions do not change in forward versus backward pedaling. J Biomech, in press
47. Neptune RR, Wright IC, Bogert AJvd: The influence of orthotics and vastus medialis strength and timing on patellofemoral loads during running. Clin Biomech, accepted
48. Nisell R, Nemeth G, Ohlsen H: Joint forces in extension of the knee. Analysis of a mechanical model. Acta Orthop Scand 57:41–46, 1986
49. Pai YC, Patton J: Center of mass velocity-position predictions for balance control. Journal of Biomechanics 30:347–354, 1997
50. Pandy MG, Anderson FC, Hull DG: A parameter optimization approach for the optimal control of large-scale musculoskeletal systems. J Biomech Eng 114:450–460, 1992
51. Pandy MG, Zajac FE: Optimal muscular coordination strategies for jumping. Journal of Biomechanics 24:1–10, 1991
52. Pearson KG, Misiaszek JE, Fouad K: Enhancement and resetting of locomotor activity by muscle afferents. Ann N Y Acad Sci 860:203–215, 1998
53. Piazza SJ, Delp SL: The influence of muscles on knee flexion during the swing phase of gait. Journal of Biomechanics 29:723–733, 1996
54. Popovic D, Stein RB, Oguztoreli N, et al: Optimal control of walking with functional electrical stimulation: A computer simulation study. IEEE Trans Rehabil Eng 7:69–79, 1999
55. Raasch CC, Zajac FE, Ma B, et al: Muscle coordination of maximum-speed pedaling. Journal of Biomechanics 30:595–602, 1997
56. Riewald SA, Delp SL: The action of the rectus femoris muscle following distal tendon transfer: Does it generate knee flexion moment? Dev Med Child Neurol 39:99–105, 1997
57. Riley PO, Kerrigan DC: Torque action of two-joint muscles in the swing period of stiff-legged gait: A forward dynamic model analysis. Journal of Biomechanics 31:835–840, 1998
58. Rugg SG, Gregor RJ, Mandelbaum BR, et al: In vivo moment arm calculations at the ankle using magnetic resonance imaging (MRI). Journal of Biomechanics 23:495–501, 1990
59. Scott SH, Engstrom CM, Loeb GE: Morphometry of human thigh muscles. Determination of fascicle architecture by magnetic resonance imaging. J Anat 182:249–257, 1993
60. Sim E: The Application of optimal control theory for analysis of human jumping and pedaling. University of Maryland, 1988, pp 1–188
61. Smith DK, Berquist TH, An KN, et al: Validation of three-dimensional reconstructions of knee anatomy: CT vs MR imaging. J Comput Assist Tomogr 13:294–301, 1989
62. Spoor CW, van Leeuwen JL: Knee muscle moment arms from MRI and from tendon travel. Journal of Biomechanics 25:201–206, 1992
63. Steinkamp LA, Dillingham MF, Markel MD, et al: Biomechanical considerations in patellofemoral joint rehabilitation. Am J Sports Med 21:438–444, 1993
64. Taga G: A model of the neuro-musculo-skeletal system for human locomotion. II Real-time adaptability under various constraints. Biol Cybern 73:113–121, 1995
65. Taga G: Does the neural system control human bipedal locomotion by preprogramming or by self-organization. Comments on Theoretical Biology 4:209–235, 1997

66. Ting LH, Kautz SA, Brown DA, et al: Phase reversal of biomechanical functions and muscle activity in backward pedaling. J Neurophysiol 81:544–551, 1999
67. Uno Y, Kawato M, Suzuki R: Formation and control of optimal trajectory in human multijoint arm movement. Minimum torque-change model. Biol Cybern 61:89–101, 1989
68. Van de Crommert HW, Mulder T, Duysens J: Neural control of locomotion: Sensory control of the central pattern generator and its relation to treadmill training. Gait Posture 7:251–263, 1998
69. van der Kooij H, Jacobs R, Koopman B, et al: A multisensory integration model of human stance control. Biol Cybern 80:299–308, 1999
70. Viegas SF, Hillman GR, Elder K, et al: Measurement of carpal bone geometry by computer analysis of three-dimensional CT images. J Hand Surg [Am] 18:341–349, 1993
71. Wang EL, Hull ML: Minimization of pedaling induced energy losses in off-road bicycle rear suspension systems. Vehicle System Dynamics 28:291–306, 1997
72. Winter DA, Pluck N, Yang JF: Backward walking—A simple reversal of forward walking. Journal of Motor Behavior 21:291–305, 1989
73. Winters JM: Hill-Based Muscle Models: A Systems Engineering Perspective. *In* Winters JM, Woo SL-Y (eds): Multiple muscle systems: Biomechanics and movement organization. New York, Springer-Verlag, 1990, pp 69–93
74. Winters JM, Stark L: Muscle models: What is gained and what is lost by varying model complexity. Biol Cybern 55:403–420, 1987
75. Wright IC, Neptune RR, Bogert AJvd, et al: Passive regulation of impact forces in heel-toe running. Clinical Biomechanics 13:521–531, 1998
76. Wright IC, Neptune RR, Bogert AJvd, et al: Validation of a 3D dynamic model of the human leg. J Biomech Eng 1999
77. Yamaguchi GT, Zajac FE: A planar model of the knee joint to characterize the knee extensor mechanism. J Biomech 22:1–10, 1989
78. Yamaguchi GT, Zajac FE: Restoring unassisted natural gait to paraplegics via functional neuromuscular stimulation: A computer simulation study. IEEE Trans Biomed Eng 37:886–902, 1990
79. Yoshihuku Y, Herzog W: Maximal muscle power output in cycling: A modelling approach. J Sports Sci 14:139–157, 1996
80. Zahalak GI: A comparison of the mechanical behavior of the cat soleus muscle with a distribution-moment model. J Biomech Eng 108:131–140, 1986
81. Zajac FE: Muscle and tendon: Properties, models, scaling, and application to biomechanics and motor control. Crit Rev Biomed Eng 17:359–411, 1989
82. Zajac FE: Muscle coordination of movement: A perspective. Journal of Biomechanics 26:109–124, 1993
83. Zajac FE, Gordon ME: Determining muscle's force and action in multi-articular movement. Exerc Sport Sci Rev 17:187–230, 1989
84. Zajac FE, Winters JM: Modeling Musculoskeletal Movement Systems: Joint and Body Segmental Dynamics, Musculoskeletal Activation, and Neuromuscular Control. *In* Winters JM, Woo SL-Y (eds): Multiple muscle systems: Biomechanics and movement organization. New York, Springer-Verlag, 1990, pp 121–148
85. Zhang YL, Hubbard M, Huffman RK: Optimum control of bobsled steering. Journal of Optimization Theory and Applications 85:1–19, 1995

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