Practical Lessons on Running and Jumping from Computer Simulations

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ABSTRACT Running and jumping are important movements for the success of athletes. Researchers in biomechanics, motor control, and sports science often use computer modeling and simulation to study the optimal performances of these movements. Simulation techniques have not been widely applied to actually assessing and improving athletic performance, although the potential for this application exists. In this review, we (1) present an introduction to the basic concepts of modeling and simulation with the athlete and coach in mind, (2) summarize the unique information that has been gained over the last 30 years from computer simulations of human running and jumping, and (3) offer suggestions on how coaches and athletes can use this information in practice to improve performance.

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1. INTRODUCTION

Running and jumping are fundamental athletic skills that are important for athletes in nearly every sport. Although situational factors and constraints influence the goals of these movements in specific instances (Glazier & Davids, 2009), in general athletes attempt to jump as high as they can or run as fast as they can. As sports scientists, coaches, and athletes, we may wonder if an athlete is achieving these goals optimally: are they really jumping as high as possible or running as fast as possible? Are they doing so in an efficient way? Are there simple (or not-so-simple) adjustments that could be made to improve performance?

There are many ways to address these questions through science and training, and indeed these questions drive the work performed by successful coaches in all sports. One approach that has been used frequently by researchers but seldom by coaches and athletes is the use of computer simulations (Hatze, 1983; Vaughan, 1984; Neptune, 2000). Therefore, the purposes of this review are (1) to provide an introductory background on musculoskeletal modeling and computer simulation so that coaches and athletes can be well-educated consumers of such research, (2) to highlight the unique information on running and jumping that has been gleaned from computer simulations of these movements, and (3) to suggest how coaches and athletes can use this information to improve athletic performance.

2. OVERVIEW ON COMPUTER MODELING & SIMULATION

While the ability to create models and perform simulations is not required to be a consumer of simulation-based research, an understanding of the terms, techniques, and procedures involved is useful for understanding the work. A model, by the most general definition, is a system that is used to represent another system. A model can be physical, conceptual, or mathematical in nature. The great majority of research in biomechanics, motor control, and sports science involves either a conceptual or mathematical model. Typically a model is much less complex than the original system so that it can be more easily understood. In general the ideal model is
The simplest one that can still address the research questions. For example, the basic flight pattern of a ball or shot can be understood by the conceptual model of an airborne object under the influence of gravity alone. A mathematical model represents the original system as a set of equations; in the ball/shot example, these equations would be the relatively simple equations of projectile motion. A computer model is a mathematical model created in the form of a computer program. Most mathematical models of human movements are also computer models because, unlike simple projectile motion, the equations are too complex to solve by hand. To study athletic performance, we can create a musculoskeletal model (Fig. 1) that represents the dynamics and control of human movement as a system of equations. While these equations are considerably more complex than the equations of projectile flight, the idea of representing a complex original system by a simpler model still holds.

Creating a musculoskeletal model involves defining equations that represent the human nervous, muscular, and skeletal systems to varying degrees of complexity (Fig. 1). In many studies cited in this review, the skeletal model was a system of rigid segments connected at joints, and the muscle models replicated classically observed input-output relationships between neural excitation and muscle force (e.g. Hill, 1938). The nervous system was not modeled explicitly but was assumed to generate the excitation signals sent to the muscles. The equations that describe the model’s dynamics (e.g. skeletal motion, muscle force production) are called the state equations. The variables input to the state equations (e.g. muscle excitations or joint torques) are called the control variables. The output movement patterns calculated by solving the state equations (e.g. joint and segment angles) are called the state variables. Parameters (e.g. muscle strengths, body segment lengths) affect the relationship between the control variables and the state variables.

Performing a simulation amounts to solving the state equations for a given set of control variables, thus producing the movement pattern (state variables) of the musculoskeletal model. One of the major strengths of computer modeling and simulation is its predictive nature: any arbitrary set of control variables can be input and the resulting motion of the model determined. However, a guess at the control variables is unlikely to produce a realistic simulation. To generate realistic and useful movement simulations, the appropriate input control variables are determined using a mathematical technique called optimization (Neptune, 1999; van Soest & Casius, 2003; Higginson et al., 2005). For example, to simulate running, Neptune et al. (2000a) optimized the magnitude and timing of input muscle excitation signals to minimize the difference between simulated and experimentally measured running movements. To simulate jumping, Anderson and Pandy (1999) optimized the muscle excitations to maximize the peak height of the jump. The optimization process is time consuming and can require days of computer processing time for complex models, even on powerful modern computing systems.

The approach used by Neptune et al. (2000a) to study running is known as “data tracking” because the goal is to replicate (“track”) a measured human movement. The data tracking

![Figure 1. The musculoskeletal modeling process is inspired by a desire to simulate a particular movement and begins with modeling the skeleton, followed by adding a system of muscle actuation and a method for controlling the muscles.](image)
approach is attractive because it explicitly generates a realistic simulation if the model is sufficiently detailed. Variables that cannot be measured in humans (e.g. muscle forces) can then be extracted from the model and related to the observed human performance. The challenge of the tracking approach is to avoid over-fitting the model with unrealistically large or under-constrained set of control variables. In contrast to the tracking approach, Anderson and Pandy (1999) used a “predictive” approach to find the muscle excitations that maximized jump height. The simulation results were compared to data from humans performing the same movement, but the simulation was not tracking these data nor was it constrained to replicate them in any way. The predictive approach is attractive because experimental data from human subjects are not strictly required to generate the simulation. Optimal performances can therefore be predicted and then compared to actual performances from human subjects. The challenge of the predictive approach is to define an appropriate criterion for optimal performance that generates a human-like movement.

3. JUMPING FOR HEIGHT

Jumping is a convenient movement to study with the predictive simulation approach because of its unambiguous optimality criterion: maximize the peak height. Once the feet leave the ground, the eventual peak height of the jump has already been determined by the vertical velocity at take-off. Some simulations of jumping have therefore maximized the vertical velocity at take-off rather than maximizing the peak height. The motivation for this choice is primarily the savings in computer processing time, since simulating only the ground contact phase requires less time than simulating both the ground contact and airborne phases.

M.F. Bobbert, a researcher at the Free University of Amsterdam, has spent much of his career studying human vertical jumping (Fig. 2). In one of the classic examples of simulations applied to sports science, Bobbert and van Soest (1994) investigated the effects of muscle strength on peak vertical jumping height. An initial simulation was performed to confirm that the model could jump in a realistic manner and to produce a set of optimal muscle excitation signals. Next, the model’s muscle strength was increased by up to 20%, and the simulation was repeated with the same excitation signals. Surprisingly, increased strength alone actually reduced the jump height. Increased strength led to higher jumps only when the muscle excitations were re-optimized to find a new set of optimal excitation patterns associated with the stronger muscles. The results indicated that adjustments in neuromuscular coordination were needed to take advantage of increased strength. The authors concluded that strength training should be accompanied by technique practice in order to optimally improve jumping ability.

In other virtual strength training studies, Cheng (2008) found that knee and ankle strength were more important than hip and shoulder strength for increasing jump height. Nagano and Gerritsen (2001) found that peak jump height was most sensitive to the strength of the knee extensor muscles (vasti). Muscle maximum shortening velocity and capacity for maximal muscle activation also substantially affected peak jump height. Experiments on human motor units and muscle fibers indicate that exercise training can alter both of these parameters (Fitts & Widrick, 1996; Gabriel et al., 2006), although it has been suggested that
maximum shortening velocity is primarily affected by endurance rather than resistance training (Malisoux et al., 2007). Jump height was maximally increased when all three parameters (strength, maximum shortening velocity, maximum activation) were increased.

The peak simulated squat jump height is sensitive to the initial depth of the squat, at least when the model is constrained to not translate horizontally (Selbie & Caldwell, 1996). Domire and Challis (2007) and Bobbert et al. (2008) both found that a deeper initial squat produced a greater peak jump height, up to 13 cm higher than jumps from more shallow squats. Interestingly, the human subjects in Domire and Challis (2007) showed no relationship between squat depth and jump height, while the subjects in Bobbert et al. (2008) showed a relationship similar to the simulations: greater squat depths produced greater jump heights. Subjects in Domire and Challis (2007) were untrained, and the authors suggested that the deep squat jumps were unfamiliar motor skills for these subjects. In contrast, subjects in Bobbert et al. (2008) were trained gymnasts. These results as a whole further support the important role for technique practice in training for the vertical jump.

The jumping studies cited so far were all simulations of squat jumping, where the model began from a static squatted posture. Humans can achieve greater peak heights when performing counter-movement jumps initiated from a more erect standing posture, with a downward movement prior to the explosive upward push-off. Bobbert et al. (1996) used their model to investigate why counter-movement jump height exceeds squat jump height. Contrary to previous theories, the storage and return of elastic strain energy in muscles is not the primary reason for increased jump height with a prior counter-movement (van Ingen Schenau et al., 1997). Rather, the presence of the counter-movement allows time for muscles to build up higher activation and force levels prior to the push-off movement.

4. JUMPING FOR DISTANCE

From a simulation perspective, jumping for distance is conceptually similar to jumping for height, except the goal is to maximize displacement horizontally rather than vertically. In one of the few examples where modeling and simulation were used to improve an individual athlete’s performance, Hatze (1981, 1983) developed a full-body musculoskeletal model and simulated the push-off phase of a long jump (Fig. 4). The initial posture of the jumper on ground contact with the take-off board and the muscle excitation signals throughout the jump were optimized to maximize the horizontal displacement of the model’s center of mass. The model’s body segmental and muscular parameters were all derived from direct or indirect measurements of a 24-year old competitive athlete with an average long-jump performance of 6.58 m and a personal-best performance of 6.96 m. The athlete’s performance was filmed and compared to the optimal performance predicted by the simulation. The model jumped further than the athlete, owing primarily to a greater angular range of hip extension and an earlier onset of hip extension during push-off. After three weeks of focused training on this technique adjustment, the athlete’s average performance improved to 7.12 m.

In the same vein of predicting optimal long-jumping technique, Ecker’s (1971) physics-based model predicted that athletes could greatly increase jumping distance by performing a forward somersault during the flight phase. The somersault technique exploits the angular momentum generated about the athlete’s center of mass during the push-off, rather than fighting against it by extending the legs as in the hitch-kick or hang techniques. Somersault jumping gained some popularity in the 1970s when an early adopter reportedly improved his long jump by more than a foot (Reid, 1974), but was eventually banned by track and field’s governing bodies when its competition
performances began to approach those of the traditional techniques (Hay, 1993). Hatze’s (1981) model, although now 30 years old, is one of the most complex and detailed musculoskeletal models in the literature. Other researchers have used much simpler models to study long jumping technique. Alexander (1990) used a simple model with a point mass at the hips, a two-segment leg, and a knee extensor muscle to investigate optimal initial push-off kinematics (approach velocity and shank angle) that maximized long jumping distance. Despite the model’s simplicity, the optimal kinematics (10 m s\(^{-1}\) and 60°) agreed well with data from actual athletes. The optimal speed and shank angle were insensitive to parameters that defined the strength and power of the knee muscle, suggesting a general optimal push-off technique (assuming the athlete can reach 10 m s\(^{-1}\), which is quite fast). Chow and Hay (2005) used a similar simple model to investigate the sensitivity of jump distance to approach velocity and leg strength. When the parameters were changed in isolation, a 10% increase in approach velocity produced a 10% increase in jump distance, and a 10% increase in leg strength produced a 7% increase in jump distance. However, when both approach velocity and leg strength were increased by 10%, the jump distance increased by 20%. The results suggest that in long jumping, the whole is greater than the sum of the parts concerning speed and strength, and that both parameters should be trained simultaneously to optimize long jumping performance.

5. SPRINT RUNNING

Sprinting, like jumping for height or distance, presents a relatively unambiguous optimality criterion: maximize speed, or equivalently, minimize the time taken to cover the sprinted distance. Simulations of sprinting (and of running in general) are few in number compared to simulations of jumping, and the determination of optimal motions and muscle excitation strategies remains a relatively new frontier in modeling and simulation.

Researchers at the University of Wisconsin Madison’s Neuromuscular Biomechanics Lab performed a series of sprinting simulations using a three-dimensional (3D) full-body model (Thelen et al., 2005; Chumanov et al., 2007, 2011). Their focus was to identify periods of the stride cycle when hamstring strain injuries are most likely to occur. The model’s joint torques were optimized to track kinematic data measured from athletes during high-speed treadmill sprinting. The torques were then distributed into individual muscle forces using so-called static optimization (Thelen et al., 2003). Analyses of muscle actions suggested that the hamstrings are most susceptible to strain injuries late in swing phase, when peak hamstring muscle fiber strains occurred while preparing the leg for ground contact. Sensitivity analyses indicated that increasing hamstring tendon compliance and strengthening the lumbo-pelvic muscles could reduce the potential for hamstring strain injuries.

In simulations performed by the authors, the muscle excitations of a 2D model (Fig. 3) were optimized to maximize the model’s average

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**Figure 3.** Computer model used by Miller et al. (2011) to simulate sprinting.
Muscular parameters were derived from joint strength tests on a group of athletic adult females. Although no measured data were tracked, the simulation compared reasonably well to joint angles and ground contact forces measured from the female runners (Fig. 4). Repeated simulations with various muscular properties removed suggested that the ability to generate muscle forces at a wide range of muscle velocities (i.e. power) is more important for sprinting than the ability to generate forces at a wide range of lengths (i.e. flexibility). However, large increases in muscle strength were needed to achieve world-class speeds.

Due to the identified importance of muscle power (force × velocity), additional simulations were subsequently performed to determine the sensitivity of sprinting speed to specific parameters that define the muscle force-velocity relationship. Speed was most sensitive to the amount of force that muscles could produce at moderate shortening velocities (Fig. 5), which is primarily a function of the fast-twitch/slow-twitch muscle fiber ratios. While training status and type of exercise can have a small effect on the relative proportions of fast- and slow-twitch fibers, the proportion of fast glycolytic (type 2B) fibers appears to be largely genetic. The results therefore suggest a muscle mechanics-based explanation for why athletes with relatively high proportions of fast-twitch fibers may be predisposed to be good sprinters.

The sprinting studies noted so far all simulated the steady-state phase of the sprint, where the athlete has reached and attempts to maintain their maximum speed. Of equal importance is the acceleration phase, where the athlete attempts to accelerate out of the starting blocks up to their maximum speed as quickly as possible. Lee and Piazza (2009) used a model of the foot and ankle to simulate the initial push-off phase out of the starting block. Decreasing the moment arm length between the Achilles tendon and the ankle joint center increased the initial speed out of the blocks by allowed the calf muscle fibers to shorten at slower velocities. Lengthening the model’s toes also increased the speed by prolonging the duration of ground contact and allowing more time to generate large propulsive forces. These findings were consistent with the anthropometrics of the competitive sprinters, who had shorter Achilles tendon moment arms and longer toes than size-matched non-sprinters.

6. ENDURANCE RUNNING
Simulating endurance running is a challenging task because the movement does not have an immediately intuitive optimality criterion. An
athlete running a mile or a marathon is not absolutely maximizing speed (else they would sprint), nor are they absolutely minimizing the metabolic cost (else they would walk). In a race, the task objectives for endurance and sprint running are similar (cover the distance in minimum time), but the endurance runner cannot absolutely maximize speed without exhausting their metabolic energy stores well before the finish line.

Wright et al. (1998) and Neptune et al. (2000a,b) avoided the optimality criterion issue by performing data tracking simulations. The muscle excitations were optimized to track the joint angles and ground contact forces measured from running humans during the stance phase. However, to avoid overestimating muscle forces and antagonistic co-activation, the permitted timings of muscle excitations were constrained to be similar to EMG signals from the same runners. The studies focused on estimating the internal muscular and joint contact forces during running and their implications for injury. Wright et al. (1998) performed tracking simulations of the impact phase (first 40 ms of ground contact) with the model of the foot-ground interface adjusted to represent either hard or soft running shoes. In agreement with data from humans running in different shoes, the magnitude of the peak external ground contact force during the impact phase was the same in both shoes, but the rate of loading increased in the harder shoe. Peak muscle forces were also sensitive to shoe type even though peak ground contact forces were not. Miller and Hamill (2009) reached a similar conclusion from tracking simulations that modeled three different shoe cushioning levels during the stance phase of running. The magnitude of bone contact forces on the distal tibia increased with increasing shoe stiffness, even though the peak ground contact force was relatively unaffected. These studies illustrate that changes in external loading do not necessarily reflect internal musculoskeletal loading. Internal loading usually cannot be measured in vivo, but can be predicted and estimated from simulations.

Neptune et al. (2000a,b) used the model of Wright et al. (1998) to simulate the entire stance phase. The first study (Neptune et al., 2000a) predicted the peak compressive joint forces near mid-stance to be 8, 12, and 9 times body weight for the hip, knee, and ankle, respectively. The second study (Neptune et al., 2000b) examined the sensitivity of predicted patellofemoral joint contact forces to commonly prescribed clinical interventions for patellofemoral pain: strength training and shoe orthotic inserts (Cutbill et al., 1997). Adding medially-wedged orthotics to the foot-ground contact model, increasing the strength of the vastus medialis muscle, or advancing the timing of vastus medialis excitation compared to vastus lateralis all decreased the peak and average lateral patellofemoral contact force. Vastus medialis strengthening consistently reduced the peak joint contact force in nine subject-specific simulations, while the effect of the orthotic intervention varied between subjects and did not always reduce the peak contact force. An additive effect was noted when all three interventions were included in the model simultaneously. The results provide biomechanical support for clinical practices in treating a common running injury. They also motivate the strength training of vastus medialis for avoiding patellofemoral pain, although it may be difficult in practice to strengthen this single muscle in isolation.

Data tracking simulations such as Neptune et al. (2000b) are useful for estimating the internal loading of the body, but compromise some of the predictive nature of simulations by requiring measured experimental data to generate the simulation. Predictive simulations of running are challenging, as noted before, because of the lack of an intuitive optimality criterion. It has been suggested humans perform movements in ways that minimize the metabolic cost (Sparrow & Newell, 1998). Measurements of metabolic energy consumed by humans while
running under various conditions have offered two general conclusions: (1) The metabolic cost (energy consumed per distance traveled) is relatively insensitive to running speed (Margaria et al., 1963), although there are conflicting reports on the specific mathematical relationship between running speed and metabolic cost (Mayhew, 1977; Steudel-Numbers and Wall-Scheffler, 2009). (2) When running at a given speed, humans select a stride length that minimizes (Cavanagh & Williams, 1982; Hamill et al., 1995) or very nearly minimizes (Morgan et al., 1994; Gutmann et al., 2006) the metabolic cost. These conclusions suggest that running does not have a well-defined, energetically-optimal speed, but that stride length at any particular speed is governed by a dynamic that maintains a low metabolic cost.

Based on these findings, the authors used the model in Fig. 3 to generate predictive simulations of endurance running (speed = 3.6-3.8 m s\(^{-1}\)) by minimizing several different criteria related to the metabolic cost: the metabolic cost itself, the level of muscle activation, or the level of muscle stress. The simulated running motions and salient descriptive data are compared in Fig. 6. Minimizing muscle activations, which avoids heavily taxing any one muscle regardless of its size or strength, predicted the most realistic metabolic cost in comparison to measurements from running humans (4.44 vs. 4.24 J m\(^{-1}\) kg\(^{-1}\); simulation 5% higher). Minimizing the metabolic cost itself, which preferentially avoids using the largest, strongest muscles that consume more energy than smaller muscles, predicted the least realistic metabolic cost, and substantially under-predicted the measured value (3.57 vs. 4.24 J m\(^{-1}\) kg\(^{-1}\); simulation 16% lower). The simulations suggest that runners adopt a muscle coordination strategy that avoids exhausting any one single muscle rather than one that absolutely minimizes the rate of metabolic energy consumption. Interestingly, the predictive simulations selected shorter stride lengths than the human subjects, regardless of which quantity was minimized. Runners who do not naturally use their energetically optimal stride length tend to over-stride (Morgan et al., 1994). The simulations therefore support the notion that runners may gain an energetic benefit by slightly reducing their stride length.

7. CONCLUSIONS ON TRAINING & CONDITIONING

This review highlighted some of the unique information on human running and jumping that
can be obtained from computer simulations of these movements. To conclude, we will suggest how coaches and athletes can use this information in their training and conditioning programs to improve performance.

The Bobbert and van Soest (1994) vertical jumping simulation suggests that resistance-training programs for improving muscular strength should be accompanied by skill practice to take full advantage of any gains in strength. This conclusion likely generalizes to long jumping, sprinting, or any movement that requires a combination of strength and skill. The suggestion that athletes engage in training protocols that improve both strength and skill is somewhat obvious, but the simulations at least provide a physiological rationale for why this is necessary. Studies that assessed the sensitivity of jumping performance to the strength of specific joints and muscle groups reported that knee extensor strength was the most important variable (Nagano & Gerritsen, 2001; Cheng, 2008). However, the greatest increase in jump height consistently occurred when the overall strength of the legs (all muscles) was increased. Overall strength is likely beneficial for avoiding injuries related to muscular imbalances as well.

In addition to muscular strength, simulations have indicated that vertical jump height is highly sensitive to the muscle fiber maximum shortening velocity (Nagano & Gerritsen, 2001; Domire & Challis, 2010). The maximum shortening velocity in human muscle fibers does not change much with resistance training, but is increased by endurance training (Fitts & Widrick, 1996; Malisoux et al., 2007). These results suggest that jumping athletes should include endurance exercise in the training programs, even if their competitive event performance does not depend directly on cardiovascular endurance.

The sprinting simulations of Chumanov et al. (2007) found that small perturbations to forces produced by lumbo-pelvic muscles during sprinting induced large increases in the peak hamstring strain. The simulation results suggest a novel and nonintuitive mechanism for hamstring strain injuries. It is difficult to infer suggestions on injury prevention and rehabilitation from this result, as it is not immediately clear how adjusting the lumbo-pelvic muscular properties would affect this sensitivity. However, since a stronger muscle can respond to an absolute perturbation level with a smaller increment in activation than a weaker muscle, it seems reasonable to suggest that strengthening the lumbo-pelvic muscles would be beneficial for preventing hamstring strain injuries.

Regarding optimal and observed sprinting techniques, our sprinting simulation (Fig. 4) ran at 6.8 m s\(^{-1}\) while the subjects upon whom the model’s parameters were based had an average maximum sprinting speed of 6.5 m s\(^{-1}\). The simulation spent less time in contact with the ground (28% of the stride) than the human sprinters (37% on average). The 12 human subjects were all fit and athletically active, but only one had any formal coaching in sprinting technique. Although we did not assess the effects of technique adjustments based on the simulation results as Hatze (1983) did, the short ground contact time in the speed-maximizing simulation is consistent with the “paw the ground” advice often used to instruct sprinters.

Predictive simulation of human endurance running is a relatively new area in computer modeling and simulation. Our assessment of the running motions generated by minimizing various criteria (Fig. 6) was driven primarily by scientific interest regarding what criteria the nervous system prioritizes when activating the muscles for running. However, the results did support the idea that some runners may gain an energetic benefit by slightly shortening their stride length (Morgan et al., 1994). Shorter strides could also be beneficial for reducing the risk of tibial stress fractures (Edwards et al., 2009). However, many runners naturally select an energetically optimal stride length when running at any particular speed (Gutmann et al., 2006), so the suggestion of adopting a shorter-
than-preferred stride length may not generalize to all runners.

One of the greatest strengths of computer simulation is the ability to expose a virtual athlete (the model) to conditions that would be impossible or unacceptable for an actual athlete. Most coaches would be unwilling to submit their athletes to an experimental protocol akin to Bobbert and van Soest (1994), in which half of the athletes would not practice at all for an extended period. Most athletes would be hesitant to participate in an in vivo version of Pandy and Zajac (1991), where gastrocnemius was changed from a two-joint muscle to a one-joint muscle. It is almost impossible to strengthen or change the force-velocity properties of an individual muscle in isolation. Yet a computer model will not object to these treatments, their effects are fully reversible, and researchers can gain insights that cannot be achieved in any human experiments.

In conclusion, simulations of human running and jumping have been tremendously useful in research environments for assessing variables that cannot be measured on live human athletes, for predicting optimal techniques by which to perform these movements, and for inferring relationships between muscular properties and movement performance. However, simulations have yet to become a common tool in coaching and athletic training. The long-jumping study described by Hatze (1983) is a rare example of a computer simulation used to directly and successfully improve athletic performance. The study was published 28 years ago, and the authors are not aware of any similar publications in the track and field literature, although simulations have been used as training aids for athletes in aerial sports such as gymnastics (Yeadon, 2008). Computer simulations have been promoted as tools for predicting clinical orthopedic and sports training outcomes since their inception in human movement science (Chow & Jacobson, 1971; Ghosh & Boykin, 1976; Hatze, 1976). The contemporary lack of this application despite strong evidence of its utility is likely due to the time required to develop and perform simulations; indeed, Hatze (1976) noted that 2300 man-hours were required to generate a subject-specific kicking simulation. However, with modern advances in high-performance computing (e.g. Anderson et al., 1995) and user-friendly simulation software (e.g. Delp et al., 2007), the raw time investment required for simulations is diminishing. An expanded role for simulations in the training of athletes will require closer collaborations between coaches, athletes, and researchers and greater efforts by researchers to promote the practical utility of simulations that are currently confined mostly to research labs.

REFERENCES
