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CAN FORWARD DYNAMIC SIMULATION MODELS BE USED TO IMPROVE THE PERFORMANCE OF TOP ATHLETES?

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The question addressed in this study was whether the forward simulation approach can be used to improve the performance of top athletes. Using a musculoskeletal model we carried out a simulation experiment on vertical squat jumping, which involved (1) generation of target kinematics, (2) production of matching simulations with two different models, (3) finding optimal solutions for the two models and (4) implementation of optimal solutions. It was shown that the approach was only successful if the model used to match the target kinematics accurately represented the system that had generated these target kinematics. Since it is not possible to make accurate models of the musculoskeletal system of individual athletes, the goal of improving the performance of top athletes with a forward dynamic simulation approach seems too ambitious.

KEY WORDS: musculoskeletal model, optimization, motor control.

INTRODUCTION: In 1981 Herbert Hatze presented a musculoskeletal model consisting of 17 body segments and 46 muscles for simulation of long jumping (Hatze, 1981). The only input of the model was the stimulation of the muscles as a function of time, which could be optimized to make the model perform a maximum-distance long jump. Hatze's groundbreaking approach, which we will henceforth refer to as forward dynamic simulation approach, has been used in numerous studies for various purposes. It has, for example, been used to estimate the mechanical output of individual muscles during activities such as jumping, cycling, walking, running and rowing, to study the effect of musculoskeletal system properties on maximum performance, to explain phenomena such as the performance enhancement effect of making a countermovement in jumping, and to study the relationship between system properties, control and performance in jumping.

In the past, most researchers have used generic musculoskeletal models. In recent years, however, researchers have taken up the challenge to make subject-specific musculoskeletal models by having individual subjects perform isometric, eccentric and concentric contractions on isovelocity dynamometers and measuring joint moments. The results obtained are used to formulate how joint moments of individual subjects vary as a function of joint angle, joint angular velocity and (voluntary) activation (Forrester et al., 2011; Yeadon et al., 2006). The stimulation input to these subject-specific musculoskeletal models may subsequently be optimized to match as close as possible kinematic data recorded during performance of a task. This approach has yielded successful matching simulations for various athletic performances, for example for running jumps for height (King et al., 2006; Wilson et al., 2007) and for the individual hop, step and jump phases in triple jumping (Allen et al., 2010).

Given that the kinematics of the performance top athletes can now be matched successfully with subject-specific musculoskeletal models, the question arises whether the forward dynamic simulation approach can also be used to improve the performance of top athletes. In the present study, we set out to answer this question by doing a simulation experiment on vertical squat jumping with a forward dynamic model.

METHODS: For simulations of jumps we used the two dimensional forward dynamic model of the human musculoskeletal system shown in Fig. 1 (top left). The model, which had muscle stimulation as its only independent input, consisted of four rigid segments representing HAT (head, arms and trunk together), thighs, shanks and feet, and was actuated by six major muscle tendon complexes (MTCs) of the lower extremity: hamstrings (HAM), gluteus maximus (GLU), rectus femoris (REC), vasti (VAS), gastrocnemius (GAS) and soleus (SOL). Each MTC was represented by a Hill type muscle model, consisting of a contractile element (CE), a series elastic element (SEE) and a parallel elastic element (PEE).

Briefly, behaviour of SEE and PEE was represented using a quadratic force-length relationship. CE force depended on CE length, CE velocity and active state. Active state, in turn, dynamically depended on muscle stimulation (STIM), a one dimensional representation of the effects of recruitment and firing rate of α-motoneurons. We simulated jumps from the preferred initial posture observed in human subjects (Bobbert et al., 2008). At the start of each simulation, the initial STIM levels were set in such a way that the resultant joint moments kept the system in static equilibrium. During push off, STIM of each muscle was allowed to increase once from its initial level towards its maximum of 1 (HAM, GLU, GAS, SOL) or towards a value between 0 and 1 (REC, VAS). The STIM-change towards a new value occurred at a rate of 5/s, which was previously used to match simulated and experimental curves in maximum height squat jumping (Bobbert et al., 2008). To solve optimization problems, we used a genetic algorithm (van Soest and Casius, 2003). If the purpose of the optimization was to match target kinematics, we minimized the root mean square (RMS) difference between the time histories of the target segment angles and the simulated segment angles. If the purpose was to maximize performance, we maximized the height reached by the centre of mass of the model.
For the simulation experiment, we used two versions of the musculoskeletal model, a reference version ($Model_{REF}$) and a version in which the maximum force of REC and VAS was reduced by 20% ($Model_{WEAK}$). The simulation experiment involved the following steps:

1. *Generation of target kinematics.* We generated target kinematic data of a submaximal squat jump with $Model_{REF}$; to make the jump submaximal we used submaximal stimulation of REC and VAS. In the real world, the target kinematic data would be kinematic data collected in the athlete whose performance is to be improved.
2. *Production of matching simulations.* We matched the kinematic data with $Model_{REF}$ and $Model_{WEAK}$. In the real world, $Model_{REF}$ would be the subject's true musculoskeletal system, and $Model_{WEAK}$ could be a musculoskeletal model derived from dynamometer experiments, in this case a model in which the maximum force of the knee extensors had been underestimated.
3. *Finding optimal solutions for the models.* We found the optimal STIM(t) that produced maximum jump height for $Model_{REF}$ and $Model_{WEAK}$. The purpose of this step was to see if improvement of performance over that in the matching simulation was possible, and if yes, to diagnose errors in the athlete's STIM(t). In the real world, the difference in kinematics between the matching simulation and the optimal solution for the model would be used to formulate an advice to the athlete for improvement of performance. This advice would presumably not be formulated in terms of activation of muscles but rather in kinematic terms (e.g. "Try to initiate knee extension earlier during the motion…").
4. *Implementation of optimal solutions.* We imposed the optimal STIM(t) found in step 3 for the two different models to $Model_{REF}$ and compared the performance with that corresponding to the target kinematics. In the real world this step would indicate whether the advice was useful.

RESULTS: Figure 1 summarizes the results obtained in the different steps of the simulation experiment. The target kinematic data of the submaximal jump, generated using $Model_{REF}$ in step 1, are shown at the top in Fig. 1. In step 2, $Model_{REF}$ could obviously match the target data exactly, but $Model_{WEAK}$ could also match them successfully (RMS error in segment angles less than 0.04 degrees). In step 3, we found the optimal solutions and the corresponding jump heights for both models; the maximum jump height of $Model_{REF}$ was 41 cm and that of $Model_{WEAK}$ was 38.1 cm. Finally, in step 4, we imposed the solutions obtained in step 3 to $Model_{REF}$. Imposing the optimal solution obtained for $Model_{REF}$ obviously reproduced the maximum height jump of this model, and imposing the optimal solution obtained for $Model_{WEAK}$ to $Model_{REF}$ resulted in a jump that was 3.2 cm below the maximum jump height. Clearly, only the use of $Model_{REF}$ in steps 2 and 3 allowed us to correctly identify that the target kinematics corresponded to a non-optimal jump, to diagnose errors, and to come up with a solution that improved jumping performance.

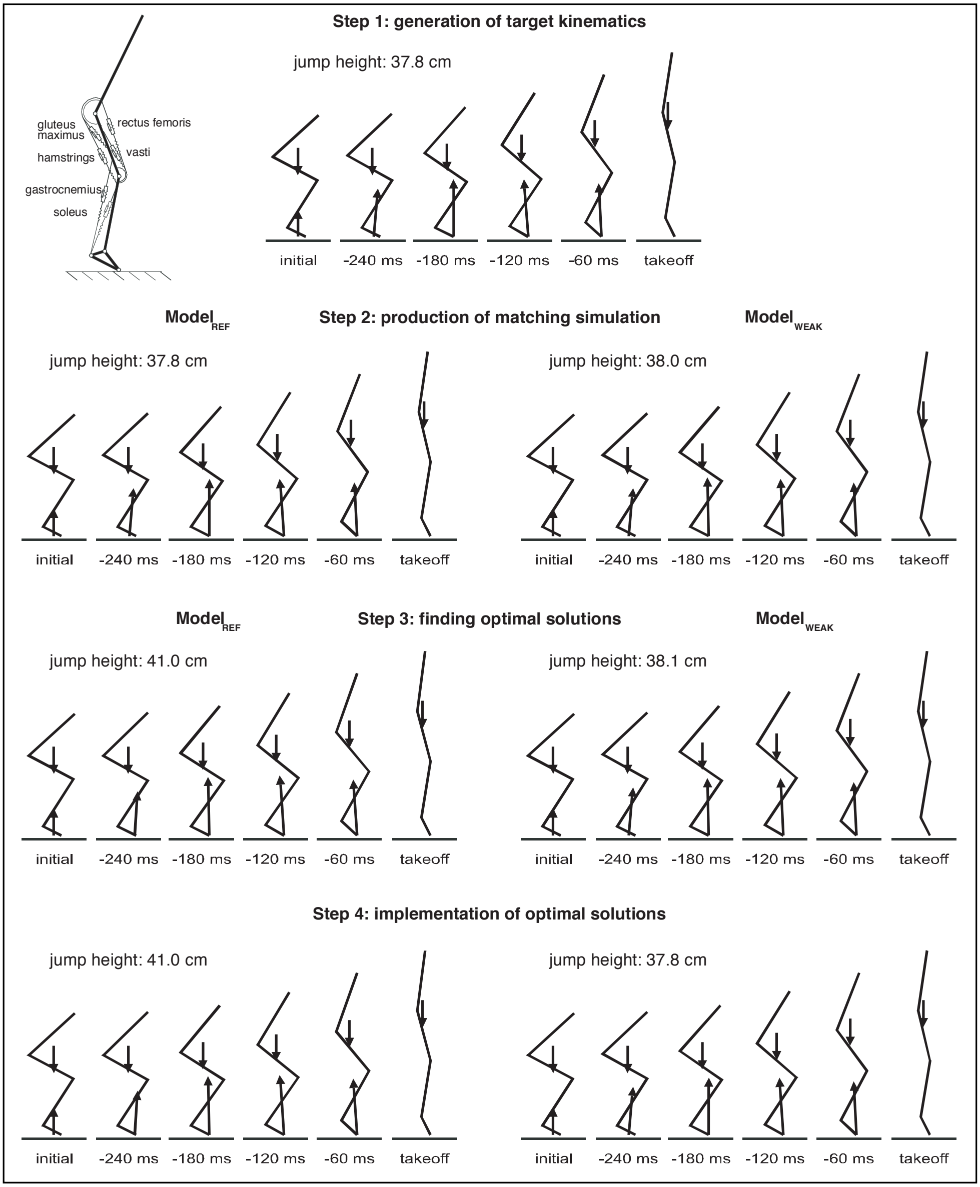

Figure 1: Forward dynamic simulation model used (top left) and results of the simulation experiment. In step 1, target kinematics were generated of a submaximal squat jump of the reference model (Model$_{REF}$). In step 2, the target kinematics were matched as close as possible using Model$_{REF}$ (left) and also with a model in which the knee extensors had been weakened by 20% (Model$_{WEAK}$). RMS differences between time histories of target segment angles and matched segment angles were below 0.04 deg. In step 3, the optimal solution was found for each of the models. In step 4, the optimal solutions obtained in step 3 were imposed on Model$_{REF}$. Jump height was defined as the height of the centre of mass at the apex of the jump relative to the height of the centre of mass in standing upright.

DISCUSSION: In this study, we set out to answer the question whether the forward simulation approach can be used to improve the performance of top athletes. We tried to answer this question by doing a simulation experiment on vertical squat jumping with a forward dynamic simulation model (Fig. 1). A performance enhancement could obviously be achieved when we used a correct model of the real system (Fig. 1, left panels), but not when we used an incorrect model (Fig. 1, left panels). In the latter case, a very good matching simulation could be obtained in step 2: the target kinematic data generated with $Model_{REF}$ could well be reproduced by $Model_{WEAK}$. However, imposing the optimal solution obtained for $Model_{WEAK}$ in step 3 on $Model_{REF}$ in step 4 did not lead to an improvement of performance (compare the result obtained in step 4 with the to-be-improved performance at the top of Fig. 1). This is not surprising because jumping requires a precise tuning of control to system properties (Bobbert and Van Soest, 1994).
The overall conclusion to be drawn from the results of this simulation experiment is that the forward simulation approach can only be used reliably to improve the performance of top athletes if one is able to accurately model the musculoskeletal system of each individual athlete. Considering that it is impossible to reliably estimate the properties of individual muscles of subjects and that even the development of subject-specific torque-driven simulation models is already quite a challenge, the goal of improving the performance of top athletes with a forward dynamic simulation approach seems too ambitious. Obviously, this does not detract at all from the power of this approach to answer “What if…?” questions that cannot be answered in experiments on subjects. Finding answers to such questions with the forward dynamic simulation approach still helps us to identify which factors are important for athletic performance (e.g. Wilson et al., 2007) and to gain a valuable understanding of why athletes move the way they do when performing their athletic skills.

CONCLUSION: The results of the simulation experiment carried out in this study lead us to be sceptical about application of the forward dynamic simulation approach with the purpose of improving the performance of individual top athletes.

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