Muscle forces during running predicted by gradient-based and random search static optimisation algorithms

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Muscle forces during locomotion are often predicted using static optimisation and SQP. SQP has been criticised for over-estimating force magnitudes and under-estimating co-contraction. These problems may be related to SQP’s difficulty in locating the global minimum to complex optimisation problems. Algorithms designed to locate the global minimum may be useful in addressing these problems. Muscle forces for 18 flexors and extensors of the lower extremity were predicted for 10 subjects during the stance phase of running. Static optimisation using SQP and two random search (RS) algorithms (a genetic algorithm and simulated annealing) estimated muscle forces by minimising the sum of cubed muscle stresses. The RS algorithms predicted smaller peak forces (42\% smaller on average) and smaller muscle impulses (46\% smaller on average) than SQP, and located solutions with smaller cost function scores. Results suggest that RS may be a more effective tool than SQP for minimising the sum of cubed muscle stresses in static optimisation.

Keywords: muscle force; optimisation; random search; running

1. Introduction

Knowledge of the forces produced by individual muscles during locomotion would be useful in applications that range from treatment of pathological gait to analysis of athletic performance. These muscle force estimates are unavailable from traditional inverse dynamics methods. The problem in determining individual muscle forces arises from the redundancy of the musculoskeletal system, whereby the number of unknown muscle, ligament and articular contact forces at a joint exceeds the number of equations of dynamic equilibrium at the joint. Such a problem is indeterminate, in that many sets of forces are capable of producing the joint moments computed from inverse dynamics. This ‘force-sharing’ or ‘general distribution’ problem is often solved using so-called static optimisation to select the set of muscle forces that both satisfies the computed joint moments and minimises a specified ‘cost function’ defined by the researcher. The set of forces is referred to as the ‘optimal solution.’ In locomotion models, the cost function is often the minimisation of the sum of muscle stresses raised to a particular power. This cost function is based on theoretical and empirical considerations of maximising muscular endurance by minimising muscle stress (Crowninshield and Brand 1981).

Muscle forces during walking and running are often computed using static optimisation implemented with quadratic programming (SQP) (Crowninshield and Brand 1981; Glitsch and Baumann 1997; Prilutsky et al. 1997; Shelburne et al. 2000; Anderson and Pandy 2001; Komura et al. 2004). Static optimisation is computationally inexpensive compared to dynamic optimisation, which uses forward dynamic simulation to find an optimal kinematic and kinetic solution to a specified performance objective. While static and dynamic optimisation can produce comparable results for walking simulations (Anderson and Pandy 2001), static optimisation and muscle stress minimisation have been criticised for over-estimating the magnitude of muscle forces (Prilutsky et al. 1997). It is possible that the prediction of overly large muscle forces is due in part to the SQP search algorithm. SQP uses a gradient-based method that always proceeds in the direction of steepest descent when searching through the domain of potential solutions to locate the optimal solution. Consequently, SQP is prone to locating a local rather than the global minimum to the cost function, and the optimal solution is sensitive to the initial guess of the researcher (Neptune 1999; Wu and Zhu 2001; Shutte et al. 2005). To find the true global minimum, an SQP algorithm must be run numerous times with different initial guesses, and for complex solution domains there is no assurance that SQP (or another algorithm) has in fact located the global minimum. As an alternative to gradient-based algorithms such as SQP, ‘random search’ (RS) algorithms increase their probability...
of locating the global minimum by searching the solution domain at random early in the optimisation, and focusing subsequent search efforts in regions where this initial seeding located promising solutions. RS algorithms include genetic algorithms (GAs), which evolve generations of solutions based on the strongest solutions from previous generations (Van Soest and Casius 2003), and simulated annealing (SA), which is based on the thermodynamics of quenched metals (Kirkpatrick et al. 1983; Higginson et al. 2005). While RS algorithms have been used previously to solve biomechanics problems (Neptune 1999; Van Soest and Casius 2003; Higginson et al. 2005), they have not been used extensively to solve static optimisation force-sharing problems. Solution domains in static optimisation force-sharing problems are often assumed to be convex with just one minimum (Crowninshield and Brand 1981), and in these situations gradient-based optimisation should be sufficient. However, it is difficult to verify convexity analytically for multi-degree-of-freedom problems (Raikova and Prilutsky 2001). In these cases, RS algorithms may be more appropriate optimisation tools than gradient-based algorithms.

An important step in any optimisation problem is the definition of the cost function. A cost function that minimises the sum of muscle stresses raised to the second or third power has been suggested as appropriate for static optimisation of muscle forces during walking and running (Crowninshield and Brand 1981; Scott and Winter 1990; Glitsch and Baumann 1997), although there is some debate over its ability to represent co-contraction (Caldwell and Chapman 1991; Gottlieb 2000). Algorithms that locate a global minimum for the cost function defined as the sum of muscle stresses cubed should be expected to predict smaller stresses (and thus smaller forces) in at least some muscles (but not necessarily all muscles) than algorithms that find a local minimum that has a higher cost function score. Because some muscles act in multiple planes or across multiple joints, changes in predicted forces could result in different patterns of co-contraction as well.

The purpose of the present study was to investigate the sensitivity of predicted muscle forces to the type of algorithm (SQP or RS) used to solve the static optimisation force-sharing problem during heel-toe running. It was hypothesised that the large muscle forces for which static optimisation has been criticised (Prilutsky et al. 1997) are due in part to the difficulty in locating the global solution with gradient-based methods, and that RS algorithms (GA and SA) would predict lower cost function scores and smaller muscle forces during the stance phase of running.

2. Methods

2.1 Subjects

Ten recreational runners (five males, five females, age 23 ± 3 years, height 174 ± 9 cm, body mass 65 ± 14 kg) were recruited and gave informed written consent. Subjects ran at least three times a week and had no history of major lower extremity disorders. The experimental protocols were approved by the university’s Institutional Review Board.

2.2 Experimental setup

Reflective marker locations were measured with an eight-camera Peak Motus motion capture system (Vicon, Centennial, CO, USA) mounted on a ring scaffold on the ceiling along a 20-m runway. Ground reaction forces were measured with an AMTI force platform (Advanced Mechanical Technologies, Inc., Watertown, MA, USA) situated at the centre of the camera ring. The camera system sampled data at 120 Hz while the force platform data were sampled synchronously at 960 Hz. Running speed was measured with a radar gun (ATS model, Stalker Radar, Plano, TX, USA).

2.3 Protocol

Subjects wore black spandex shirt and shorts and their own running shoes. Reflective markers were placed on the subject’s dominant leg (Figure 1), defined as the leg with which they would kick a soccer ball. Three non-co-linear markers were placed on each of the foot, calf, thigh and pelvis segments, allowing computation of three degrees of rotational freedom for each segment (Miller et al. 2007). A static calibration trial was performed with the subject standing in the anatomical position at the centre of the ground.
camera ring. Subjects completed seven trials of running down the 20-m runway over the force platform while the camera system recorded marker locations. Successful trials were defined as ones in which the subject struck the force platform with their entire dominant foot only and ran within ±5% of their preferred speed, defined as the average speed in three preliminary trials.

2.4 Data reduction and modelling

Marker coordinates and force platform output were digitised with a 12-bit A/D converter. A fourth-order zero-lag low-pass Butterworth filter was applied to marker (15 Hz cutoff) and force (75 Hz cutoff) data. Stance time was defined from heel-strike to toe-off, determined from the vertical GRF using a threshold force of 50 N. Three-dimensional joint angles during stance were computed using the Euler angle method of Hamill and Selbie (2004). Sagittal plane joint moments at the hip, knee, and ankle were computed using inverse dynamics (Bresler and Frankel 1950). Segment inertial parameters were estimated according to de Leva (1996). Joint moments and angles during stance were interpolated to 101 points by cubic splines. Ensemble curves for each subject’s joint moments and angles were computed by averaging the interpolated data from each trial.

Ensemble joint angles were exported to a musculoskeletal model of the lower extremity (SIMM 4.1, MusculoGraphics, Inc., Santa Rosa, CA, USA) that contained nine bones (pelvis, sacrum, femur, tibia, fibula, patella, talus, calcaneus and metatarsals), scaled to the leg length of each subject. The model included 18 musculo-tendon units: semimembranosus (SEM), long and short heads of biceps femoris (BF lh, BF sh); the superior, middle and inferior components of gluteus maximus (GM sc, GM mc and GM ic), iliacus (ILI), rectus femoris (RF), vastus lateralis (VL), vastus medialis (VM), vastus intermedius (VI), medial and lateral heads of gastrocnemius (GA mh, GA lh), soleus (SO), tibialis posterior (TP), tibialis anterior (TA), peroneus longus (PL) and extensor digitorum longus (EDL). For each subject, the model computed sagittal plane muscle lengths and moment arms during stance from the input joint angle data.

2.5 Optimisation

Muscle forces for each subject were computed using static optimisation with each of the three algorithms: SQP, GA, and SA. At each 1% interval of stance, the algorithms found the set of muscle forces that minimised the cost function \( CF \) defined as the sum of cubed muscle stresses:

\[
CF = \sum_{m=1}^{18} \left( \frac{F_m}{PCSA_m} \right)^3, \tag{1}
\]

where \( F_m \) is the muscle force and \( PCSA_m \) is the physiological cross-sectional area of the muscle, estimated from SIMM according to Zajac (1989). Possible muscle force estimates were limited by an inequality constraint that required muscle forces between zero and a predicted upper bound \( UB_m \):

\[
0 \leq F_m \leq UB_m, \tag{2}
\]

where \( UB_m \) is the muscle’s force based on its force–length and force–velocity relationships (Wilkie 1950; Gordon et al. 1966; Hill 1970) assuming the muscle was maximally activated. Values for \( UB_m \) were computed using a three-component Hill muscle model with contractile (CC), series elastic (SEC) and parallel elastic components. Maximum isometric muscle forces, optimal CC lengths, muscle force–velocity parameters, SEC stiffness and unloaded SEC lengths scaled to the body mass and leg length of the subject were taken from SIMM. An equality constraint required that the muscles crossing each joint satisfied the joint moments computed by inverse dynamics at each 1% of stance:

\[
\sum_{m=1}^{18} r_{mj} F_m = M_j, j = 1, 2, 3, \tag{3}
\]

where \( r_{mj} \) is the sagittal moment arm of muscle \( m \) at joint \( j \) and \( M_j \) is the sagittal plane resultant joint moment at joint \( j \) computed from inverse dynamics.

SQP optimisation was implemented using the ‘fmincon’ function in the MATLAB Optimisation Toolbox (The MathWorks 2006). SQP proceeds at each iteration in the search direction of ‘steepest descent’ such that the magnitude of the cost function decreases. Thus, SQP can become trapped if a search direction leads to a local optimal solution. The optimal solution in SQP occurs when the partial derivatives of the solution with respect to the search direction approach zero. SQP required an initial guess for the muscle forces at each interval of stance. At heel-strike, the initial guess for all forces was zero. At each subsequent interval, the initial guess was the solution from the previous interval. SQP solutions were also obtained with the GA and SA solutions input as the initial guess.

GA optimisation was implemented using the ‘ga’ function in the MATLAB Genetic Algorithm and Direct Search Toolbox (The Mathworks 2006). GA creates a random initial population of solutions and selects solutions with low cost function scores as ‘parents’ of the next generation of solutions. The best parents are chosen as ‘elite’ members who survive into the next generation of solutions. Averaging the solution vectors of a pair of parents produces normal ‘children’, but mutant children can arise by inducing random changes to the solution of a single parent. By this element of randomness, GA avoids becoming trapped in local minima. The generational process repeats until the specified maximum number of
generations is reached, at which time the solution with the lowest cost function score is taken as the optimal. SA optimisation was implemented in MATLAB code-based on the method of Kirkpatrick et al. (1983). SA is based on the thermodynamics of metallurgical quenching, where the metal’s molecules arrange themselves in the lowest-energy state. In searching for an optimum, SA considers neighbour solutions of the current solution as it steps along its search path through the solution domain. To decide whether to move to a neighbour solution, SA uses a probability function-based on relative cost function scores and a ‘temperature’ parameter whose value decreases over time. SA avoids local minima because the probability function sometimes chooses to move to a neighbour solution even though it has a higher cost function score than the current solution. Thus, the SA algorithm promotes wide searching across the solution domain to avoid becoming trapped in a local solution. As the temperature falls, the probability of moving to a more costly neighbour solution decreases and approaches zero, prompting the algorithm to move downhill to the global optimal solution.

Optimisations were performed on a 3 GHz Pentium® D CPU (Intel Corp., Santa Clara, CA, USA) with 3.75 GB of memory. To ensure fair comparisons, the termination criteria for SQP, GA and SA were adjusted such that each algorithm searched the solution domain for approximately the same CPU time (16,000 s per subject). This CPU time was found to be sufficient for the RS algorithms to converge, with no further improvements in the cost function (<1%) from additional iterations.

2.6 Outcome variables

Each muscle’s peak force was extracted from the force–time curve during stance. Muscle impulses were computed by integrating the muscle’s force–time curve during stance. Muscle impulses and peak forces were expressed relative to subject body weight.

Muscular co-contraction (MCC) at each joint was calculated as the ratio of the sums of antagonistic muscle forces (i.e. flexors vs. extensors) at each time step and averaged over early, mid and late stance (0–33, 34–67 and 68–100% of stance time, respectively). For each ratio, the larger sum (flexor or extensor) was always used as the numerator to ensure that the ratio was always greater than or equal to one:

\[
MCC_{ij} = \max \left( \frac{\sum F_{\text{flex}}}{\sum F_{\text{ext}}}, \frac{\sum F_{\text{ext}}}{\sum F_{\text{flex}}} \right)_{i}, \quad j = 1, 2, 3, \quad (4)
\]

where \(\sum F_{\text{flex}}\) and \(\sum F_{\text{ext}}\) represent the algebraic sums of forces in flexor and extensor muscles at the joint, respectively, \(i\) represents the interval of stance and \(j\) represents the joint in question. By this definition, smaller ratios closer to one indicate higher levels of co-contraction than larger ratios. Flexors and extensors were defined in an anatomical sense; for example, muscles that cross the knee anteriorly were defined as knee extensors, and muscles that cross the knee posteriorly were defined as knee flexors. The amount of co-contraction was classified into one of four categories based on the magnitude of MCC. ‘High’ co-contraction was defined as MCC between 1 and 5, ‘Medium’ co-contraction as MCC between 5 and 20 and ‘Low’ co-contraction as MCC between 20 and 100. No co-contraction was assumed for ratios higher than 100, or when force levels were near zero for all involved muscles. The classifications were based on the co-contraction data for all subjects and algorithms. The three ranges were selected because co-contraction ratios were clustered within each range.

Figure 2. Resultant joint moments (solid line) computed by inverse dynamics (Inv Dyn) and joint moments generated by the muscle forces predicted by SQP (solid squares) and GA (open circles) for (a) hip, (b) knee and (c) ankle.
2.7 Statistical analysis

Muscle impulses and peak forces were compared between algorithms by one-way ANOVA. Main effects were analysed by post hoc matched-pair t-tests with Tukey adjustments for multiple comparisons, with each subject’s GA and SA muscle force compared to their SQP muscle force as the matched pair. Differences were considered significant at the $\alpha = 0.05$ level.

3. Results

Figure 2 shows the resultant joint moments from inverse dynamics (right-hand side of equation (3), compared with the joint moments computed by summing the products of estimated muscle forces and their moment arms about each joint ([left-hand side of equation (3)]). Data are for a representative subject; the other nine subjects had similar results. Moments for GA and SA were nearly identical, and only GA moments are shown. For each subject, the average root mean square error per time step between each of the algorithms and the inverse dynamics net joint moments was less than 0.2 Nm, indicating that all three algorithms were successful in satisfying the equality constraint equation (3).

Figure 3 shows muscle force profiles for one subject computed by SA for muscles crossing the hip (Figure 3(a), knee (Figure 3(b)) and ankle (Figure 3(c)). In early stance, the hamstrings and GM were active to absorb the impact and prevent the hip from flexing. In mid stance, the vasti and triceps surae were active to extend the knee and plantarflex the ankle, propelling the body forward. In late stance, all muscle forces declined and dropped to lower levels at toe-off. GA and SA predicted lower cost function scores than SQP across the entire stance phase (Figure 4), and predicted nearly identical solutions for all subjects. Therefore, only SA results are shown, and we will refer to RS to represent the results of both GA and SA. When the SQP algorithm was run with an RS solution as its initial guess at each time step, SQP located the GA or SA solution.

Group muscle impulse and peak force data computed by SQP and RS are shown in Table 1. RS predicted smaller peak forces than SQP for all muscles. The greatest between-algorithm differences in peak force were in Ili, TA, and EDL (RS 82, 81 and 81% smaller than SQP, respectively). The smallest difference was in RF (8% smaller). When averaged across all subjects and all muscles, peak RS forces were 42% smaller than peak SQP forces. RS predicted smaller impulses than SQP for all muscles except RF, which was 16% larger. On average, RS impulses were 46% smaller than SQP impulses. Differences in peak force and impulse between search
algorithms were statistically significant \((p < 0.05)\) for all muscles except RF.

Both SQP and RS predicted co-contraction at the hip, knee and ankle during the three phases of stance (Figure 5). RS predicted higher levels of co-contraction than SQP in six of the nine joint-stance phase combinations. SQP predicted higher levels of co-contraction than RS only during late stance at the ankle joint.

### Table 1. Muscle impulses and peak forces during the stance phase of running computed by SQP, SA and GA.

<table>
<thead>
<tr>
<th>Muscle</th>
<th>Peak muscle forces (BW)</th>
<th>Muscle impulse (100 BW s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>SQP</td>
<td>SA</td>
</tr>
<tr>
<td>SEM</td>
<td>1.92 (0.60)</td>
<td>1.22 (0.40)</td>
</tr>
<tr>
<td>BF (lh)</td>
<td>1.19 (0.47)</td>
<td>0.75 (0.27)</td>
</tr>
<tr>
<td>BF (sh)</td>
<td>0.19 (0.13)</td>
<td>0.04 (0.04)</td>
</tr>
<tr>
<td>GM (sc)</td>
<td>0.39 (0.13)</td>
<td>0.28 (0.14)</td>
</tr>
<tr>
<td>GM (mc)</td>
<td>0.73 (0.25)</td>
<td>0.49 (0.19)</td>
</tr>
<tr>
<td>GM (ic)</td>
<td>0.49 (0.17)</td>
<td>0.34 (0.18)</td>
</tr>
<tr>
<td>ILI</td>
<td>0.39 (0.37)</td>
<td>0.07 (0.07)</td>
</tr>
<tr>
<td>RF</td>
<td>0.48 (0.21)</td>
<td>0.44 (0.15)</td>
</tr>
<tr>
<td>VM</td>
<td>2.01 (0.44)</td>
<td>1.32 (0.22)</td>
</tr>
<tr>
<td>VI</td>
<td>2.24 (0.48)</td>
<td>1.45 (0.25)</td>
</tr>
<tr>
<td>VL</td>
<td>3.51 (0.78)</td>
<td>2.31 (0.41)</td>
</tr>
<tr>
<td>GA (nh)</td>
<td>1.33 (0.29)</td>
<td>0.94 (0.19)</td>
</tr>
<tr>
<td>GA (lh)</td>
<td>0.39 (0.09)</td>
<td>0.28 (0.06)</td>
</tr>
<tr>
<td>SO</td>
<td>5.70 (1.11)</td>
<td>4.03 (0.74)</td>
</tr>
<tr>
<td>TP</td>
<td>0.97 (0.19)</td>
<td>0.68 (0.12)</td>
</tr>
<tr>
<td>TA</td>
<td>0.41 (0.20)</td>
<td>0.08 (0.06)</td>
</tr>
<tr>
<td>PL</td>
<td>0.45 (0.35)</td>
<td>0.24 (0.04)</td>
</tr>
<tr>
<td>EDL</td>
<td>0.17 (0.08)</td>
<td>0.03 (0.02)</td>
</tr>
</tbody>
</table>

Forces and impulses were normalised to body weight (BW). Data are mean (SD) for 10 subjects. The ‘%’ column is the percent difference between the mean of SA and GA values versus the SQP value, relative to the SQP value. All differences between SQP and RS were statistically significant \((p < 0.05)\) except for rectus femoris (RF) results.

### Figure 5. Degrees of co-contraction at the hip, knee, and ankle in early stance (0–33%), mid stance (34–67%) and late stance (67–100%). ‘High’ co-contraction indicates an antagonistic force ratio between 1 and 5. ‘Medium’ indicates a ratio of 5 and 20. ‘Low’ indicates a ratio of 20–100. ‘None’ indicates a ratio greater than 100. Black represent SQP data. White represents RS data.

### 4. Discussion

The present results demonstrate that predictions of muscle forces during the stance phase of running using static optimisation are sensitive to the type of algorithm used to solve the force-sharing problem. Specifically, RS algorithms predicted smaller muscle forces than the gradient-based SQP algorithm by locating more optimal cost function scores when solving the same problem (Figure 4). These findings were consistent for all 10 subjects in the study.

The results address two of the major cited shortcomings for using static optimisation and minimisation of total muscle stress to estimate muscle forces during locomotion: the over-estimation of muscle force magnitudes (Prilutsky et al. 1997) and the under-estimation of muscular co-contraction (Caldwell and Chapman 1991; Gottlieb 2000). The RS algorithms predicted smaller peak muscle forces than SQP for all 18 muscles in the model, and predicted smaller impulses than SQP for all muscles except RF. Interestingly, only RF did not show a substantial reduction in peak force when using RS algorithms. Peak RF force decreased by only 8%, while the other muscles averaged a 42% decrease. The RF impulse actually increased with RS algorithms (+16%), while the impulses of all other muscles decreased (~46% on average). This result seems to indicate that RF impulse was used to satisfy the joint moment constraints at the hip and knee when impulses in other muscles crossing these joints decreased. Such a result may highlight the unique contribution of bi-articular muscles to lower extremity...
motion in running, a contribution that is apparent even in sub-optimal solutions. Previous research has demonstrated the importance of bi-articular muscles such as RF during running for regulating net joint moments and transferring energy within the leg (Jacobs et al. 1993; Efftman 1940). Hanon et al. (2005) found that RF was one of the first muscles to show electromyographic signs of fatigue during an exhaustive run.

While both RS and SQP predicted muscular co-contraction, RS computed more realistic patterns (Figure 5). In particular, RS results at the ankle were superior to SQP when qualitatively compared to muscle electromyography (EMG) profiles from the literature Gazendam and Hof (2007). Co-contraction at the ankle is a function of co-activity of the ankle dorsiflexors (TA and EDL) and plantarflexors (SO, GA and TP). Previous research on muscle EMG during running has indicated that the TA is active during late swing and very early stance, and is quiet for the majority of stance (Perry 1992). Meanwhile, triceps surae activity is prevalent in early stance, peaks in mid stance, and then declines during late stance (Perry 1992; Gazendam and Hof 2007). Consequently, early stance is the only time at which both the TA and the triceps surae are highly active, and thus displaying a strong degree of co-contraction. The RS algorithms correctly predicted high ankle co-contraction in early stance only, with none in mid and late stance. Most of this co-contraction was due to the RS algorithms using GA to contribute to the small knee flexor moment in early stance (Figure 2(b)). In contrast, SQP satisfied the knee flexor moment in early stance using knee flexors other than GA, and predicted no ankle co-contraction in early and mid stance, and medium co-contraction in late stance. However, it should be noted that the muscle forces from which these levels of ankle co-contraction in early stance are calculated were quite small. This finding should therefore not be interpreted as a major shortcoming of the SQP algorithm.

In the context of the present methodology, conclusions on muscular co-contraction should be made with the operational definition of co-contraction in mind. Co-contraction was defined as the ratio of forces generated by muscles whose architecture and geometry causes them to generate opposing moments at the same joint equation (4). However, the coupled nature of body segments allows muscles to induce accelerations at joints they do not span and segments they do not touch (Zajac et al. 2002). Thus, the contributions of a muscle to joint actions are not limited to the joints the muscle spans. Perhaps the concept of ‘co-contraction’ at a joint needs revision, because the co-activation of muscles may be related to separate, independent actions to which each muscle contributes. This is particularly evident for bi-articular muscles. The contributions of individual muscles to the accelerations of individual joints and segments cannot be computed with the present static optimisation due to the incomplete set of equations solved (specifically, the upper body and contralateral leg were neglected). In future research, whole-body muscle-actuated forward dynamic models would be useful in further deducing the function of individual muscles during running.

Although researchers have used numerical methods to estimate muscle forces for several decades, the methods have not been widely adopted in clinical settings, in part due to the difficulty in validating the methods. While the patterns of muscle force in the present results agree well with patterns in muscle EMG activity from other studies (Jacobs et al. 1993; Hanon et al. 2005; Gazendam and Hof 2007), EMG alone does not provide a measure of actual force, and ignores important considerations such as muscle force–length and force–velocity relationships (Wilkie 1950; Gordon et al. 1966; Hill 1970). While muscle forces can be measured during in vivo movement (Komi 1990), the methods are invasive or impractical in clinical settings, and limited to superficial tendons such as the Achilles. Until more practical measurement techniques become available, numerical estimations of muscle forces will remain difficult to validate. However, the close agreement between EMG literature and the present muscle forces (low TA force across stance, consistent GM activity during stance, large triceps surae and vasti forces) suggest that muscle forces predicted by static optimisation may be a reasonable estimate of in vivo muscle forces (Prilutsky et al. 1997).

In all 10 subjects, the two RS algorithms predicted nearly identical muscle force profiles and cost function scores, suggesting that the RS algorithms were locating solutions near the global minimum to the cost function, whereas SQP located a local minimum. If SQP was provided the RS solution as its initial guess at each time step, SQP also located this solution (all three curves in Figure 4 fell on top of each other), indicating that the three algorithms where in fact searching the same solution space. However, only the RS algorithms located this minimum without a priori knowledge of the solution. It is possible to search for the global minimum using only SQP by running multiple simulations with a variety of initial guesses at each time step. However, this method negates the only advantage of SQP over RS algorithms (speed), and there is still no assurance that SQP has located the global minimum without using an exhaustive array of initial guesses (although this criticism is technically true of RS algorithms as well; the true global minimum cannot be assured with any numerical method). When solving optimisation problems with a large number of unknown variables and complex solution domains, it is recommended based on the present results that an RS algorithm be used to better approach the global minimum.

The present study was limited by the exclusion of joint moments in secondary planes. Previous research has indicated that muscle force estimates are sensitive to the
number of degrees of freedom allowed at the joints (Glitsch and Baumann 1997). However, that study used a sprinting motion and included over twice as many muscles as the present study, many of which functioned primarily in secondary plane motion, whereas the muscles in the present study functioned primarily in the sagittal plane. The decision to focus on the sagittal plane and on a smaller set of muscles was made in order to simplify the force-sharing problem and thereby reduce the CPU time. The degree-of-freedom problem in static optimisation has been studied in greater detail by Glitsch and Baumann (1997). In our pilot work with a larger set of 47 muscles and three degrees of freedom at each joint, the solution time was prohibitively long. This more complex model predicted similar results at the sagittal hip and knee, but very large forces (15–20 times body weight) for the ankle plantar flexors, possibly due to the lack of a defined subtal joint, and had difficulty reproducing the knee joint moments in the secondary planes, possibly due to a lack of direct muscle actuation controlling knee ab/adduction and transverse rotation. Previous research has demonstrated that frontal plane ankle moments do not accurately represent subtalar mechanics during running (O’Connor and Hamill 2005). Future research should consider the effects of the definition of joint axes on predictions of muscle forces.

Low computational cost is the main advantage of the static optimisation/inverse dynamics approach used in the present study compared to a dynamic optimisation/forward dynamics approach. As computers become progressively more powerful and affordable, computational cost will become less of a limitation. Forward dynamic modelling offers several advantages over inverse dynamic modelling in terms of detailed muscle mechanics information and the ability to predict novel and optimal movement patterns. However, static optimisation has the advantage of offering a faster and simpler method of investigating how the body activates muscles and distributes internal loads across multi-muscle systems.

In summary, RS algorithms found more optimal solutions than the gradient-based SQP algorithm for a force-sharing problem during the stance phase of running, and thus improved static optimisation results by predicting smaller muscle force magnitudes and more realistic patterns of co-contraction. The algorithms searched the same solution domain under the same constraints and had the same computational resources. Differences in solutions must therefore be attributed to the methods by which the algorithms searched the solution domain and settle upon a converged solution. When using static optimisation, care must be taken in selecting an algorithm, and in defining constraints, cost functions, and their interactions to make sense in terms of the physiology of the problem. In an optimisation problem where the goal is to minimise the muscle stresses during running, the RS algorithms GA and SA are more suitable than the gradient-based algorithm SQP.

References


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