Proceedings of the ASME 2016 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference
IDETC/CIE 2016
August 21-24, 2016, Charlotte, North Carolina

DETC2016-59107

MUSCLE FORCE PREDICTION OF 2D GAIT USING PREDICTIVE DYNAMICS OPTIMIZATION

Yujiang Xiang*
Department of Mechanical Engineering
University of Alaska Fairbanks
Fairbanks, AK 99775
*Email: yxiang@alaska.edu

ABSTRACT

Cyclic human gait is simulated in this work by using a 2D musculoskeletal model with 12 degrees of freedom (DOF). Eight muscle groups are modeled on each leg. Predictive dynamics approach is used to predict the walking motion. In this process, the model predicts joints dynamics and muscle forces simultaneously using optimization schemes and task-based physical constraints. The results indicated that the model can realistically match human motion, ground reaction forces (GRF), and muscle force data during walking task. The proposed optimization algorithm is robust and the optimal solution is obtained in seconds. This can be used in human health domain such as leg prosthesis design.

1 INTRODUCTION

Digital human modeling and simulation have attracted considerable attention in recent years with specific emphasis on the ability to predict human biomechanics for real-life applications. Many biomechanical models have been suggested toward this end [1-4]. There are several novel approaches that predict motion based on solving an optimization problem formulated by defining appropriate performance measures and constraints to recover the real motion of a biomechanical system [5-10]. Predictive dynamics (PD) [11] is one of the performance optimization methods for predicting and simulating human motions. This work extends author's previous walk motion prediction to a 2D musculoskeletal model under the predictive dynamics framework. All predictive dynamics advantages can be utilized to predict muscle forces for human gait.

Thelen et al. [12] and Thelen and Anderson [13] proposed the computed-muscle control (CMC) method in which the joint torques were obtained from feedback control and then a static optimization was performed to calculate muscle forces. Ackermann and van den Bogert [14] studied the muscle activation performance measure for dynamic walking motion prediction using a 2D musculoskeletal model. The direct collocation method was used to formulate the optimization problem in which the state variables, controls, and muscle activations were all treated as design variables. More work on muscle modeling, motion prediction using musculoskeletal models, and muscle functionality analyses during the dynamic walking motions is described in review papers [15-17].

Our goal in this study is to simulate and analyze muscle forces of a 2D gait model. The symmetric walking motion prediction is formulated as a nonlinear optimization problem (NLP). The control points of the B-splines for the joint angle profiles and muscle force profiles are treated as the design variables. For the performance measure, the multi-objective optimization (MOO) of dynamic effort, which is represented as the integral of the sum of the squares of all the normalized joint torques and the normalized muscle force squares, is minimized using a sequential quadratic programming algorithm (SQP) [18]. Results of the optimization problem are the GRF, torque, joint angle, and muscle force profiles.

2 SKELETAL MODEL

The musculoskeletal model of this work is defined in the joint space with 12 DOF. 3 DOF are used for global translation and rotation and 9 DOF are used for the kinematics of the body as shown in Figure 1. The model consists of three physical branches and one virtual branch including global DOF. The physical branches include the right leg, left leg, and spine. This model is developed by using Denavit-Hartenberg (DH) method [19]. The musculoskeletal model of lower limb and muscle properties were adopted from Ackermann [20] as seen in Figure 2. Eight muscle groups were considered on each leg; they are Ilio, RF, Glu, Ham, Vas, Gas, TA, and Sol. The anthropometric data for the skeletal model representing a 50th percentile male is generated using GEBOD software [21].

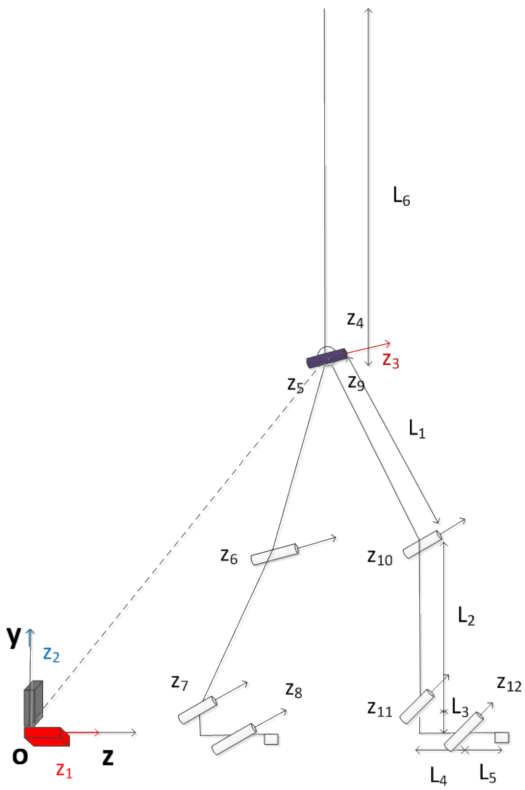


Figure 1. The 2D gait model

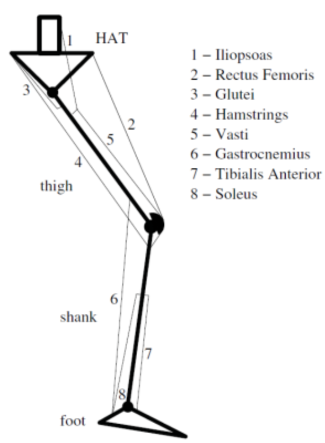


Figure 2. Musculoskeletal model of lower extremity

3 KINEMATICS AND DYNAMICS

The general equations of motion for a multi-link rigid body system can be written as [22]:

$$\boldsymbol{\tau} = \mathbf{M}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{V}(\mathbf{q},\dot{\mathbf{q}}) + \sum_i \mathbf{J}_i^T m_i \mathbf{g} + \sum_k \mathbf{J}_k^T \begin{bmatrix} -\mathbf{F}_k \\ -\mathbf{M}_k \end{bmatrix} \qquad (1)$$

where $\boldsymbol{\tau}$ is the actuator torque vector, $\mathbf{M}(\mathbf{q})$ is the generalized mass-inertia matrix, $\mathbf{V}(\mathbf{q},\dot{\mathbf{q}})$ is the Coriolis and centrifugal force vector, $\mathbf{J}_i$ is the Jacobian matrix of the position vector for the center of mass of ith link, $\left[\mathbf{F}_k^T, \mathbf{M}_k^T\right]^T$ are the external loads (forces and moments) applied to the point at ${}^k\mathbf{r}_k$ (location of point on link k expressed in the local frame of link k), and $\mathbf{J}_k$ is the augmented Jacobian matrix of the position vector ${}^k\mathbf{r}_k$.

Because of its computational efficiency [23], recursive formulation is used in this work to calculate the kinematics and dynamics of the skeletal model. The forward kinematics transfers the motion from the origin towards the end-effector along the branch. In contrast, the backward dynamics propagates forces from end-effector to the origin. The joint torques are computed using the recursive Lagrangian formulation. Therefore, the computational cost is reduced to the order of O(n), where n is the number of DOF. In addition, the closed-form analytical gradients are provided for the kinematics and dynamics variables for use in the optimization process [24].

A two-step active-passive algorithm is used to calculate GRF. The basic idea is to obtain GRF from the equilibrium conditions between the resulting active forces and GRF at zero moment point (ZMP) which is defined as a point on the ground where the tangential moments are zero. Details of the algorithm were provided by [25, 26] and outlined here as follows:

(1) Given state variables q, $\dot{q}$, $\ddot{q}$ (design variables) for each DOF, the global resultant active forces ($\mathbf{M}^o$, $\mathbf{F}^o$) at the origin in the inertial reference frame (o-xyz in Figure 1) are obtained from equations of motion using inverse dynamics.

(2) After that, the ZMP position is calculated from its definition using the global resultant active forces as follows:

$$y_{zmp} = 0;\ x_{zmp} = 0;\ z_{zmp} = -M_x^o / F_y^o \qquad (2)$$

where $\mathbf{M}^o = [M_x^o \quad M_y^o \quad M_z^o]^T$ and $\mathbf{F}^o = [F_x^o \quad F_y^o \quad F_z^o]^T$. In addition, the two feet are assumed on the level ground.

(3) After obtaining the ZMP position, the resultant active forces at ZMP ($\mathbf{M}^{zmp}$, $\mathbf{F}^{zmp}$) are computed using the equilibrium condition as follows:

$$\begin{aligned} \mathbf{M}^{zmp} &= \mathbf{M}^o + {}^o\mathbf{r}_{zmp} \times \mathbf{F}^o \\ \mathbf{F}^{zmp} &= \mathbf{F}^o \end{aligned} \qquad (3)$$

where ${}^o\mathbf{r}_{zmp}$ is the ZMP position in the global coordinate system obtained from Eq. (2).

(4) Then, the value and location of GRF are calculated from the equilibrium between the resultant active forces and passive forces at the ZMP:

$$
\begin{aligned}
&\mathbf{M}^{GRF} + \mathbf{M}^{zmp} = \mathbf{0} \\
&\mathbf{F}^{GRF} + \mathbf{F}^{zmp} = \mathbf{0} \\
&{}^{o}\mathbf{r}_{GRF} - {}^{o}\mathbf{r}_{zmp} = \mathbf{0}
\end{aligned}
\tag{4}
$$

(5) Finally, all active forces (gravity, inertia and external forces) and passive forces (GRF) are applied to the multibody human system to obtain the joint torques that are used in the constraints and objective function.

4 OPTIMIZATION FORMULATION

4.1 Design variables

The joint angle profiles are represented by 4th order B-spline control points $\mathbf{P}_4$. The muscle force profiles are represented by cubic B-spline control points $\mathbf{P}_3$. Both joint angle and muscle force control points are defined as design variables for the walking motion as $\boldsymbol{x} = [\mathbf{P}_4, \mathbf{P}_3]$. Joint torques are calculated inversely from joint angle profiles based on equations of motion.

4.2 Objective function

The normalized dynamic effort, which is defined as the time integral of the squares of all normalized joint torques and the normalized muscle force squares, was chosen as the objective function to be minimized for walking movement:

$$
f = \sum_{i=1}^{n} \int_{t=0}^{T} \left(\frac{\tau_i(\mathbf{P}_4, t)}{\tau_i^U - \tau_i^L} \right)^2 dt + \sum_{i=1}^{m} \int_{t=0}^{T} \left(\frac{f_i(\mathbf{P}_3, t)}{f_i^{max}} \right)^2 dt \tag{5}
$$

where τ_i^U and τ_i^L are upper and lower joint torque limit for the ith joint; f_i^{max} is the maximum muscle force for the ith muscle; n is the number of DOF; m is the number of muscles; T is the total time.

4.3 Constraints

The general constraints are categorized into physical constraints and task-based constraints. Physical constraints include the joint angle limits, joint torque limits, muscle force limits, and muscle force torque equilibrium as depicted in the following equations:

$$\mathbf{q}^L \le \mathbf{q}(t) \le \mathbf{q}^U \tag{6}$$

$$\boldsymbol{\tau}^L \le \boldsymbol{\tau}(t) \le \boldsymbol{\tau}^U \tag{7}$$

$$0 \le \boldsymbol{f}(t) \le \boldsymbol{f}^{max} \tag{8}$$

$$R\boldsymbol{f}(t) = \boldsymbol{\tau} \tag{9}$$

where the superscript L denotes the lower bound, and U denotes the upper bound, R is the constant moment of arm of muscle forces [20]. The joint angle limits are given in Xiang et al. [25] and the join torque limits are given in Xiang et al. [27].

The task-based constraints being used to generate the symmetric gait motion include ground penetration, balance (ZMP) condition, feet contacting positions, ground collision avoidance, and symmetry conditions for joint angle and muscle forces [25].

5 RESULTS

The appropriate walking parameters are obtained from motion capture experiment [28]. The walking speed is v = 1.2 m/s, and step length L = 0.6 m. Two strides of the simulated 2D gait from left heel strike to the subsequent left heel strike is shown in Figure 3. The joint torque profiles are depicted in Figure 4. Figure 5 shows the predicted GRF profiles. The muscle forces on left leg for a gait cycle including stance phase and swing phase are depicted in Figure 6. The developed algorithm based on the predictive dynamics approach was robust and the optimal solution was obtained in about 30 seconds.

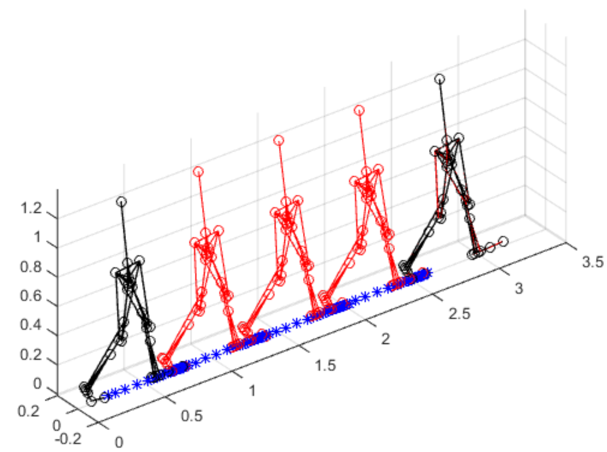
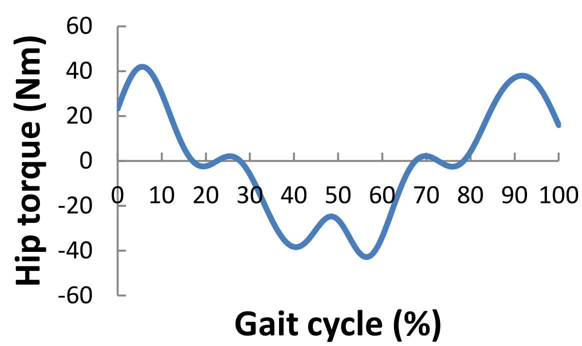
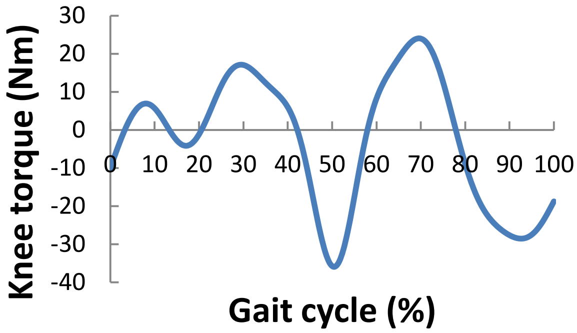


Figure 3. 2D stick diagram of gait (* is ZMP)



(a)



(b)

Figure 4. Joint torque profiles: (a) hip, (b) knee

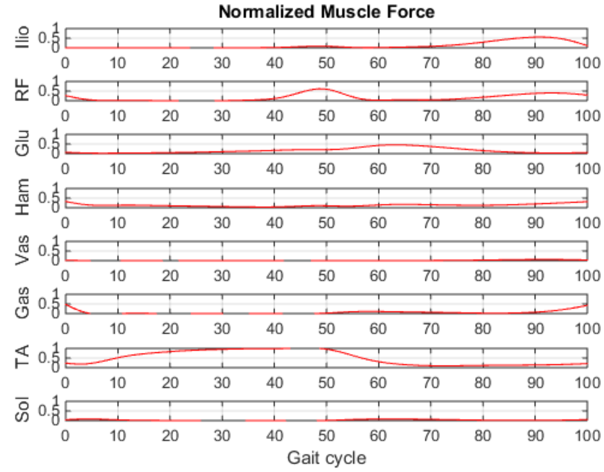
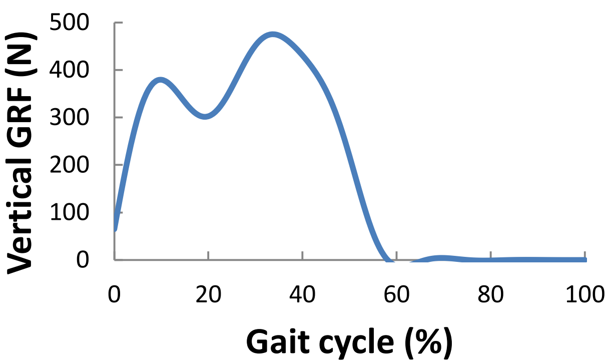
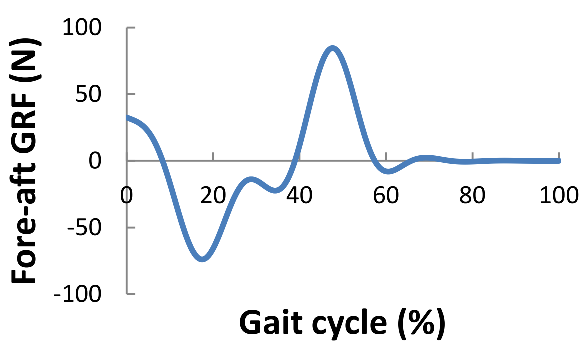


Figure 6. Normalized muscle forces in a gait cycle



(a)



(b)

Figure 5. GRF in a gait cycle: (a) vertical, (b) fore-aft

6. DISCUSSION

In Figure 3, continuous 2D human walking motion is simulated with symmetry conditions on joint angle, velocity, and acceleration. Due to higher order B-spline curves are used to interpolate the joint angle profiles, the hip and knee torques in Figure 4 have similar initial and final values for a complete gait cycle. This is quite important for making the muscle force symmetry constraints feasible.

Figure 5 shows reasonable vertical and fore-aft GRF compared the data available in the literature. Muscle forces in Figure 6 are generated to balance joint torque in an optimal way by minimizing the cost function Eq. (5). In this study muscle force squared is considered as a human performance measure. The predicted muscle forces show general agreement with the literature and more rigorous validation is required for muscle force prediction.

In summary, the 2D gait motion planning problem was formulated as an optimization problem. Minimization of the torques at all joints and muscle force squares were used as the objective function subjected to physical and kinematics constraints. The transition between left and right steps is satisfied by imposing the symmetry constraints. Torque, joint angle, GRF, and muscle force profiles were obtained to analyze the walking motion. Optimization-based 2D gait prediction reveals great insights in the real human walking motion. For future work, muscle activations will be modeled using an inverse approach [29, 30] in the current optimization formulation.

7. ACKNOWLEDGEMENT

This research work was partly supported by the Alaska NASA EPSCoR Program (NNX13AB28A).

8. REFERENCES

[1] Xiang, Y., Arora, J.S., and Abdel-Malek, K., 2011. Optimization-based prediction of asymmetric human gait. Journal of Biomechanics, 44(4), 683–693.

[2] Shourijeh, M.S., and McPhee, J., 2014. Optimal control and forward dynamics of human periodic motions using fourier series for muscle excitation patterns. J. Comput. Nonlinear Dynam., 9, 021005.

[3] Kim HJ, Wang Q, Rahmatalla S, Swan CC, Arora JS, Abdel-Malek K, Assouline JG., 2008. Dynamic motion planning of 3D human locomotion using gradient-based optimization. Journal of Biomechanical Engineering, 130(3):031002.

[4] Xiang, Y., Arora, J.S., Abdel-Malek, K., 2010c. Physics-based modeling and simulation of human walking: a review of optimization-based and other approaches. Structural and Multidisciplinary Optimization, 42(1), 1-23.

[5] Chevallereau, C. and Aoustin, Y. 2001. Optimal reference trajectories for walking and running of a biped robot. Robotica 19: 557-569.

[6] Mu, X. P. and Wu, Q. 2003. Synthesis of a complete sagittal gait cycle for a five-link biped robot. Robotica 21: 581-587.

[7] Bessonnet, G., Marot, J., Seguin, P., Sardain, P. 2010. Parametric-based dynamic synthesis of 3D-gait. Robotica, 28(4), 563-581.

[8] Ren, L., Jones, R. K., Howard, D. 2007. Predictive modelling of human walking over a complete gait cycle. Journal of Biomechanics 40(7): 1567-1574.

[9] Fregly, B.J., Reinbolt, J.A., Rooney, K.L., Mitchell, K.H., Chmielewski, T.L. 2007. Design of patient-specific gait modifications for knee osteoarthritis rehabilitation. IEEE Transactions on Biomedical Engineering, 54(9), 1687-1695.

[10] Anderson FC, Pandy MG., 2001. Dynamic optimization of human walking. Journal of Biomechanical Engineering, 123(5), 381–390.

[11] Xiang, Y., Chung, H.J., Kim, J.H., Bhatt, R., Rahmatalla, S., Yang, J., Marler, T., Arora J.S., Abdel-Malek, K., 2010. Predictive dynamics: an optimization-based novel approach for human motion simulation. Structural and Multidisciplinary Optimization, 41(3), 465–479.

[12] Thelen DG, Anderson FC, Delp SL, 2003. Generating dynamic simulations of movement using computed muscle control. J. Biomech., 36(3):321–328.

[13] Thelen, D. G. and Anderson F. C., 2006. Using computed muscle control to generate forward dynamic simulations of human walking from experimental data. J Biomech, 39(6): 1107-15.

[14] Ackermann M, van den Bogert AJ, 2010. Optimality principles for model-based prediction of human gait. J Biomech, 43(6):1055-60.

[15] Erdemir A, McLean S, Herzog W, van den Bogert AJ, 2007. Model based estimation of muscle forces exerted during movements. Clin Biomech 22:131–154.

[16] Pandy MG, 2001. Computer modeling and simulation of human movement. Annu Rev Biomed Eng 3:245–273.

[17] Zajac FE, 1989. Muscle and tendon: properties, models, scaling, and application to biomechanics and motor control. Crit Rev Biomed Eng 17(4):359–411.

[18] Gill, P.E., Murray, W., and Saunders, M.A., 2002. SNOPT: An SQP algorithm for large-scale constrained optimization. SIAM J. Optim. 12, 979-1006.

[19] Denavit J, Hartenberg RS, 1955. A kinematic notation for lower-pair mechanisms based on matrices. ASME J Appl Mech 22:215–221.

[20] Ackermann, M., 2007. Dynamics and energetics of walking with prostheses. PhD thesis, University of Stuttgart, Germany.

[21] Cheng, H., Obergefell, L., Rizer, A., 1994. Generator of body (GEBOD) manual, AL/CF-TR-1994-0051. Armstrong Laboratory, Wright-Patterson Air Force Base, Ohio.

[22] Fu, C., Tan, F., and Chen K., 2010. A simple walking strategy for biped walking based on an intermittent sinusoidal oscillator. Robotica, 28, 869–884.

[23] Hollerbach, J.M., 1980. A recursive Lagrangian formulation of manipulator dynamics and a comparative study of dynamics formulation complexity. IEEE Transactions on Systems, Man, and Cybernetics, 11(10), 730-736.

[24] Xiang, Y., Arora, J.S., Abdel-Malek, K., 2009. Optimization-based motion prediction of mechanical systems: sensitivity analysis. Structural and Multidisciplinary Optimization, 37(6), 595-608.

[25] Xiang, Y., Arora, J.S., Rahmatalla, S., Abdel-Malek, K., 2009. Optimization-based dynamic human walking prediction: one step formulation. International Journal for Numerical Methods in Engineering, 79(6), 667-695.

[26] Kim, J.H., Xiang, Y., Bhatt, R., Yang, J., Chung, H.J., Arora, J.S., and Abdel-Malek, K. (2009) Generating effective whole-body motions of a human-like mechanism with efficient ZMP formulation. International Journal of Robotics and Automation, 24(2),125-136.

[27] Xiang, Y., Arora, J.S., Chung, H.J., Kwon, H.J., Rahmatalla, S., Bhatt, R., Abdel-Malek, K. 2012. Predictive simulation of human walking transitions using an optimization formulation. Structural and Multidisciplinary Optimization, 45(5): 759-772.

[28] Inman VT, Ralston RJ, Todd F., 1981. Human Walking. Wilkins & Wilkins: Baltimore, MD.

[29] Schiehlen, W., and Garcia-Vallejo, D., 2012. 3D-simulation of human walking by parameter optimization. Arch Appl Mech, 82, 533-556.

[30] Shourijeh, MS, and McPhee, J., 2014. Forward dynamic optimization of human gait simulations: a global parameterization approach. J. Comput. Nonlinear Dynam., 9, 031018.

