MULTI-OBJECTIVE OPTIMIZATION OF IMPEDANCE PARAMETERS IN A PROSTHESIS TEST ROBOT

Poya Khalaf
Department of Mechanical Engineering
Cleveland State University
Cleveland, Ohio 44115
Email: p.khalaf@vikes.csuohio.edu

Hanz Richter∗
Department of Mechanical Engineering
Cleveland State University
Cleveland, Ohio 44115

Antonie J. van den Bogert
Department of Mechanical Engineering
Cleveland State University
Cleveland, Ohio 44115

Dan Simon
Department of Electrical and Computer Engineering
Cleveland State University
Cleveland, Ohio 44115

ABSTRACT
We design a control system for a prosthesis test robot that was previously developed for transfemoral prosthesis design and test. The robot’s control system aims to mimic human walking in the sagittal plane. It has been seen in previous work that trajectory control fails to produce human-like forces. Therefore, we utilize an impedance controller to achieve reasonable tracking of motion and force simultaneously. However, these objectives conflict. Impedance control design can therefore be viewed as a multi-objective optimization problem. We use an evolutionary multi-objective strategy called Multi-Objective Invasive Weed Optimization (MOIWO) to design the impedance controller. The multi-objective optimization problem admits a set of equally valid alternative solutions known as the Pareto optimal set. We use a pseudo weight vector approach to select a single solution from the Pareto optimal set. Simulation results show that a solution that is selected for pure motion tracking performs very accurate motion tracking (RMS error of 0.06 cm) but fails to produce the desired forces (RMS error of 70% peak load). On the other hand, a solution that is selected for pure force tracking successfully tracks the desired force (RMS error of 12.7% peak load) at the expense of motion trajectory errors (RMS error of 4.5 cm).

INTRODUCTION
In recent years the development of prosthetic devices has progressed rapidly. However a major problem of designing prostheses is the ability to test newly developed devices in normal and hazardous test conditions on human subjects. Problems such as informed consent, safety harnesses and the lack of repeatability across tests, hinder the design and testing process of prosthetic devices. Robotic test devices can overcome these problems and also provide additional benefits such as operating continuously for long periods of time and working in conditions that are unsafe for patients [1]. In the last few years a robotic test platform has been developed and used for the purpose of transfemoral prosthesis design and testing [2]. The test robot developed aims to mimic human walking in the sagittal plane by simulating the hips vertical and the thighs angular motions. However the main challenge of using a robotic platform for the design and development of prostheses is designing a control system that can imitate the behavior of a human subjects. Currently the control

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system that is being used in this test robot is trajectory control for the hips vertical and the thighs angular motions. The results of implementing trajectory control on the robot have proven to provide perfect trajectory control but fail to reproduce the forces that would have been produced in a human testing platform. In order to overcome this problem Davis et al. [3] have used an evolutionary algorithm to optimize the desired trajectories that the trajectory control follows in order to minimize the error between the ground reaction force (GRF) of able bodied gait data and that of the robot. In addition they postulate that the optimized trajectory could emulate the hip and thigh motion of an amputee while wearing a prosthesis. The result of their study showed significant improvement in the ground reaction force of the robot but still noticeable deviations were seen in the GRF profile compared to the gait data. In addition the GRF that the prosthetic device produces is a result of its overall dynamic performance and matching the GRF resulting from the leg prosthesis to the GRF of that produced by an able body does not seem to be a reasonable method to test the prosthesis. Noble et al. [4] have taken a similar approach and used iterative optimization to adjust the joint motion trajectory profiles to eliminate offsets between the actual and target load responses.

In this study we take another approach and use a mixed motion and force control strategy, namely impedance control [5], in order to achieve reasonable tracking of motion and force simultaneously. An impedance controller regulates the dynamic relationship between force and motion of a robot at its ports of interaction with the environment [6].

For the purpose of designing an impedance controller, we use able bodied gait data for the trajectories of the hip and thigh and we use the vertical component of the force exerted on the hip of an able body as the desired force profile that should be exerted on the robots hip. However these objectives are often conflicting and a more desirable force tracking can lead to a less desirable motion tracking. Therefore the problem of designing an impedance controller to track a desired force trajectory and a desired motion trajectory can be viewed as a multi-objective optimization problem.

The multi-objective optimization problem admits a set of equally valid alternative solutions which are known as the Pareto-Optimal set. These solutions are such that improvement in any objective can only be achieved at the expense of degradation in other objectives, and can only be discriminated on the basis of expert knowledge about the problem. Thus, in a multi-objective optimization procedure, ideally the effort must be made in finding the set of tradeoff optimal solutions by considering all objectives to be important. After a set of such tradeoff solutions are found, a user can then use higher-level qualitative considerations to select a final solution from the obtained Pareto set [7].

Classical gradient based optimization algorithms are prone to getting trapped in a local optimum and need an initial condition close to the final solution [8]. In addition evolutionary algorithms work with a population of solutions in each iteration which makes them intuitive for multi-objective optimizations [9]. Therefore in this study an evolutionary multi-objective strategy namely the Multi-Objective Invasive Weed Optimization (MOIWO) algorithm has been used. The Invasive Weed Optimization (IWO) algorithm was proposed by Mehrabian and Lucas in 2006 [10]. This algorithm draws inspiration from the natural behavior and colonization of weeds and has been successfully used for the purpose of designing controllers for nonlinear systems [11, 12]. Therefore in this study, we use the multi-objective extension of the IWO for the purpose of designing an impedance controller [13].

The rest of this paper is organized as follows:

In the mathematical modeling section we discuss the equations of the test robot with the attached leg prosthesis. In the controller design section the architecture of the controllers used are explained. In the next section we discuss the methods used for deriving the desired force and motion trajectories from human motion test data. In the MOIWO algorithm section the optimization algorithm used is briefly discussed. In the next section the problem is formulated as a multi-objective optimization problem. Finally in the results section the results of simulating the controllers performance is discussed.

Mathematical Modeling
The test robot aims to mimic the movement of a human hip. It has two degrees of freedom, the hip vertical displacement and the thigh rotary displacement. A DC servo motor and transmission are responsible for controlling each degree of freedom. Both servo motors have an encoder fitted on them that provide position and velocity feedback. The prosthetic device is attached to the robot above the knee joint also a treadmill provides a moving surface for the robot to walk on.

Figure 1 shows a schematic of the test robot with the attached prosthesis. The Mauch MicroLite S Knee [14] and a flexible prosthetic foot which is rigidly attached to the shank, are used as the attached prosthesis. The robot and the attached prosthesis are modeled as a three link robot. Since the leg prosthesis is passive and the knee torque cannot be controlled externally, the system is considered to be underactuated. The dynamic model of the test robot with the attached passive prosthesis is given in joint coordinates by:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + B\dot{q} + n(q, \dot{q}) + F_f + J_T^T F_e = \begin{bmatrix} \frac{K_{act}}{0} \end{bmatrix}$$

where $q^T = [q_1, q_2, q_3]$ is a vector of joint displacements, $q_1$ is the hip vertical displacement, $q_2$ is the thigh angular displacement and $q_3$ is the knee angular displacement, $M(q)$ is the mass matrix, $C(q, \dot{q})$ accounts for centripetal and Coriolis effects, $n(q, \dot{q})$ is the nonlinear damping vector of the knee damper, $B$ is a viscous
damping matrix, $F_f$ is a vector of Coulomb friction terms, $J_e$ is the kinematic Jacobian relative to the external forces $F_e$, $g(q)$ is the gravity vector, $K_a$ is the diagonal matrix of actuator gains and $u_a$ is a vector of control inputs. The nonlinear damping vector $n(q, \dot{q})$, can be calculated as
\[ n^T = [0, 0, \partial R/\partial \dot{x}_d] \]
where $R$ is the Rayleigh dissipation function:
\[ R = \frac{1}{2} b_k \dot{x}_d \]
where $b_k$ is a direction dependent damping coefficient and $\dot{x}_d$ is the expansion rate of the damper. Also $b_k$ has been estimated using an experimental procedure. Details about deriving the test robot model and the robot parameters used in this paper can be found in [2]. The foot and ground interaction is modeled by defining two contact points for the foot, the heel and the toe. If the ground is defined as the line of $Y = 0$, the vertical ground reaction force at each contact point is calculated as:
\[ F_Y = \begin{cases} 0 & Y \geq 0 \\ -k_2Y & Y < 0 \end{cases} \]
where $X$ is defined in the direction of motion, $X_{rel}$ is the relative velocity of the points of contact with respect to the treadmill and $\gamma$ is the friction coefficient. Also $v_0$ must be small enough to approximate the Coulomb friction. Table 1 gives the parameters used for this model.

### CONTROLLER DESIGN

In this section the controllers used for the hip’s vertical and the thigh’s angular motions are explained. Since the rotary actuator of the robot which is responsible for providing the thighs angular motion is not backdrivable, the effect of the hips vertical motion on the thigh’s angular motion can be neglected in designing the thigh controller. The errors due to this simplification in the thigh controller’s design can be overcome by the robustness of the thigh controller. In this study we use a robust Sliding Mode controller for the thigh’s angular movements and an impedance controller for the hip’s vertical motion. Each of these two controllers are explained in the next two subsections.

#### Impedance Control

The test robot control system currently is a decoupled sliding mode trajectory control for the hip vertical motion and the thigh angular motion. In this study we aim to replace the sliding mode controller of the hip’s vertical motion with an impedance controller which can also track a desired force profile as well as a desired motion trajectory profile in order to better simulate the behavior of an actual human subject. The equation of motion for the hip joint is given by:
\[ M_1(q_1)\ddot{q}_1 + f_1(\dot{q}_1) + g_1(q_1) = K_1 u_1 + F_{int} \]
where $q_1$ is the hip’s vertical displacement, $M_1$ is the inertia matrix, $f_1$ is the friction term, $g_1$ is the gravity term, $K_1$ is a constant reflecting a combination of servo amplifier gain, motor torque

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_2$ (Nm$^{-1}$)</td>
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</tr>
<tr>
<td>$\gamma$</td>
<td>1</td>
</tr>
<tr>
<td>$v_0$ (ms$^{-1}$)</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Coulomb friction force and is described as [15]:
\[ F_X = -\gamma F_Y \left( \frac{2}{1 - e^{-\frac{X_{rel}}{v_0}}} - 1 \right) \]

Table 1. PARAMETERS USED FOR FOOT MODEL.
constant and rotary/linear motion conversion, $u_1$ is the control voltage and $F_{int}$ is the vertical component of the interaction force exerted on the hip joint. The desired impedance is specified as:

$$M_m(q_1 - \dot{q}_{1d}) + C_m(\dot{q}_1 - \dot{q}_{1d}) + K_m(q_1 - \dot{q}_{1d}) = \lambda_1 (F - F_d)$$

where $M_m, B_m, K_m$ are the desired inertia damping and stiffness respectively, $q_{1d}$ is the desired motion trajectory and $F_d$ is the desired force trajectory. By computing $\dot{q}$ from Eqn. (6) and replacing it in Eqn. (5) the control input is derived as:

$$
u_1 = \frac{1}{K_1} \frac{M_1}{M_m} (M_m \ddot{q}_{1d} + K_1 (F - F_d) - C_m (\dot{q}_1 - \dot{q}_{1d}) - K_m (q_1 - q_{1d}) + f_1 + g_1 - F_{int})$$

The parameters $M_m, B_m, K_m$ and $K_f$ will be tuned using an optimization scheme which is described in the next section.

### Sliding Mode Control

A Sliding Mode controller (SMC) [16] is designed for the thigh’s angular motion. The SMC is known for its robustness properties and its straightforward implementation [2]. The equation for the rotary actuator of the robot’s thigh is specified as:

$$J_2 \ddot{q}_2 + b_2 \dot{q}_2 = K_2 u_2 + \tau$$

where $q_2$ is the thigh’s angular position, $u_2$ is the control voltage of the thigh actuator, $K_2$ is a constant reflecting a combination of servo amplifier gain and motor torque constant, $J_2$ is the inertia of the load and motor, $b_2$ is the viscous damping constant. $\tau$ represents an uncertain torque term consisting of actual external load, parameter uncertainties, disturbances and unmodeled dynamics. Equation (8) admits a sliding function of the form $s = \dot{e} + \lambda e$ where $e = q_{2d} - q_2$ is the tracking error and $\lambda > 0$ is a constant. The SMC control law for the thigh angular motion is derived as:

$$u_2 = \frac{J_2}{K_2} \left[ (\dot{q}_{2d} + \lambda \dot{q}_{2d}) + \frac{b_2}{J_2} - \lambda \dot{q}_2 + \eta \text{sign}(s) \right]$$

where $\eta > 0$ is chosen according to a bound for $\tau$. Table 2 gives the values of the parameters used for the sliding mode controller. In the next section we use motion capture data from a human subject in order to derive the desired force and motion trajectories for the hip and thigh controller.

<table>
<thead>
<tr>
<th>$\eta$</th>
<th>$\lambda$</th>
</tr>
</thead>
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<tr>
<td>100</td>
<td>40</td>
</tr>
</tbody>
</table>

### GENERATING FORCE AND MOTION TRAJECTORIES

In this section we aim to generate the desired force and motion trajectories for the controllers described in the previous section from human motion capture test data. The motion capture data were collected from the laboratory for Human Motion and Control at Cleveland State University by placing markers on the different segments of the human subjects body and collecting marker trajectories with the use of motion capture cameras. In addition force plates were used to gather ground reaction force data. From the marker data the vertical displacement of the hip and the angular motion of the thigh were derived. The trajectories were filtered with a second order Butterworth filter with a cutoff frequency of 10 Hz and are shown in Fig. 2 and Fig. 3. Also the velocities and accelerations of the hip and thigh are derived by differentiating the position trajectories. Winter’s approach [17] is used for deriving the vertical component of the force acting on the hip. The anthropometry table from Winter [17] was used to derive the mass of each body segment with respect to total body mass. Also the center of mass trajectory of each body segment was calculated from the marker data using the methods of Winter [17]. By differentiating the center of mass trajectories twice, the center of mass acceleration is derived for each body segment. By using the center of mass acceleration of each body segment and the ground reaction force data a recursive calculation sequence is started from the foot to solve for the proximal force and moment of each body segment. This calculation is continued up to the hip where the force acting on the hip is derived. Figure 4 shows the vertical component trajectory of the force acting on the hip. In the next section the Multi Objective Invasive Weed Optimization algorithm is briefly discussed.

### THE MOIWO ALGORITHM

In a multi-objective optimization problem there are multiple conflicting objectives which result in a set of alternative solutions called Pareto Optimal solutions, or non-dominated solutions. Thus in a multi-objective optimization problem one must initially strive to find the Pareto Optimal solutions and in the next step utilize a decision-making scheme for choosing the most preferred solution from the Pareto optimal solutions. In regards of finding Pareto optimal solutions, any multi-objective optimization algorithm must be capable of finding a set of solutions which are Pareto optimal and are diverse enough to represent the entire...
range of the Pareto optimal solutions [18].

The MOIWO algorithm starts by initializing a population which is spread randomly over the dimensions of the solution space. After evaluating the fitness of each individual, a dominance ranking [18] scheme is used and each individual is assigned a rank where individuals with rank=1 are non-dominated. In the next step the MOIWO uses the crowding distance (CD) [9] assignment in order to maintain the diversity of the population. Following the calculation of the rank and CD, the weakness (opposite of fitness) of each individual is calculated as specified by:

\[
weakness = rank + \frac{1}{CD + 2}
\]  

(10)

In the next step of the MOIWO algorithm, the population is sorted according to the weakness of each individual. Sorting the population with respect to its weakness ensures that individuals are initially sorted according to their rank and the individuals with the same rank are sorted according to their CD. Thereafter each member of the population produces seeds (offspring) depending on its own and the populations highest and lowest weakness. The number of seeds for each individual is computed linearly with respect to its weakness and the maximum and minimum number of possible seeds by:

\[
S = \left( \frac{S_{\text{max}} - S_{\text{min}}}{W_{\text{max}} - W_{\text{min}}} \right) (W - W_{\text{min}}) + S_{\text{max}}
\]  

(11)

where \( S \) is the number of seeds, \( S_{\text{max}} \) and \( S_{\text{min}} \) are the maximum and minimum number of seeds respectively, \( W \) is the individuals weakness and \( W_{\text{max}} \) and \( W_{\text{min}} \) are the maximum and minimum weaknesses in the population respectively. Figure 5 shows the process of seed reproduction. The generated seeds are then distributed over the solution space by normally distributed random numbers with mean equal to zero, but varying standard deviation. The standard deviation at each iteration of the MOIWO algorithm is calculated by:

\[
\sigma_{\text{iter}} = \left( \frac{\sigma_{\text{max}} - \sigma_{\text{iter}}}{\sigma_{\text{max}}} \right) n (\sigma_{\text{initial}} - \sigma_{\text{final}}) + \sigma_{\text{final}}
\]  

(12)

where \( \sigma_{\text{initial}} \) and \( \sigma_{\text{final}} \) are the initial and final value of the standard deviation respectively, \( \sigma_{\text{iter}} \) is the current value of standard deviation, \( \sigma_{\text{max}} \) is the maximum number of iterations and \( n \) is the nonlinear modulation index. Finally when the maximum
number of seeds in a population is reached, a competitive exclusion mechanism activates to eliminate the seeds with poor fitness to reach the maximum allowable population. Also in order to prevent the loss of good solutions during the optimization process due to random effects, an archive elitism approach is incorporated in the MOIWO algorithm [19]. For more information regarding the MOIWO algorithm refer to [13]. The pseudo code for the MOIWO algorithm is summarized as follows:

1. Initialize a population
2. Fitness evaluation
3. Assign ranking of each individual
4. Assign CD of each individual
5. Compute weakness of each individual
6. Compute the number of seeds corresponding to each individual weakness
7. Distribute the seeds over the search space
8. If maximum population is reached perform competitive exclusion
9. Repeat 2-8 until stopping criterion is fulfilled

OPTIMIZATION VIA THE MOIWO ALGORITHM

For providing optimum operation of the controller, the tracking of motion and tracking of force should be optimized simultaneously. These objectives are often conflicting in nature and the optimization of one objective may result in the degradation of the other objectives. Therefore in this study we utilize a multi-objective optimization algorithm namely the MOIWO algorithm. The objective functions are defined as:

$$
objective = \left[ \frac{\sum_{i=1}^{T} (F_i - F_d)^2}{T} \times 10^{-3} \right]^{1/2}
$$

(13)

where $F$ and $F_d$ are the interaction force and desired interaction force respectively, $T$ is the number of sample points. Also $q_{1d}$ and $q_{1d}$ are the vertical position and desired position of the robot’s hip joint.

The equations of the prosthesis test robot and the equations of the hip and thigh controllers are simulated using Matlab’s Simulink. Also the fourth order Runge Kutta method (ODE4) is used for solving the systems equations. The MOIWO algorithm changes the impedance controller’s gains and simulates the test robot model’s performance iteratively until the maximum number of iterations is achieved. Table 3 shows the parameters used for the MOIWO in this study. It should be noted that the optimization process has been run several times using different parameters in order to ensure the convergence of the optimization algorithm to the Pareto optimal solutions. After finding a set of Pareto optimal solutions, the question of selecting a single preferred solution from the Pareto optimal set for implementation on the test robot’s controller becomes important. Here a pseudo weight vector approach [7] has been used for this purpose. In the pseudo-weight vector approach a pseudo weight vector is calculated for each solution. The dimension of the weight vector is equal to the number of objectives. The weight for the $i^{th}$ objective for a minimization problem is calculated according to [7]:

$$
w_i = \frac{(f^\text{max}_i - f_i)}{(f^\text{max}_i - f^\text{min}_i)} \sum_{m=1}^{M} \left( \frac{f^\text{max}_m - f_m}{f^\text{max}_m - f^\text{min}_m} \right)
$$

(14)

where $f^\text{max}_i$ and $f^\text{min}_i$ are the maximum and minimum values of each of the objective functions respectively and $M$ is the number of objectives. $w_i$ represents the relative distance of each solution from its maximum value in each objective function. Furthermore the sum of all weight components of the weight vector corresponding to a specific solutions, are equal to one. After calculating the weight vector for each solution, the solution which has a weight vector closer to the user-preferred weight vector is

<table>
<thead>
<tr>
<th>Table 3. PARAMETERS USED FOR MOIWO ALGORITHM</th>
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<tbody>
<tr>
<td>Quantity</td>
</tr>
<tr>
<td>Number of initial population</td>
</tr>
<tr>
<td>Maximum number of iteration</td>
</tr>
<tr>
<td>Maximum number of plants</td>
</tr>
<tr>
<td>Maximum number of seeds</td>
</tr>
<tr>
<td>Minimum number of seeds</td>
</tr>
<tr>
<td>Nonlinear modulation index</td>
</tr>
<tr>
<td>Initial value of standard deviation</td>
</tr>
<tr>
<td>Final value of Standard Deviation</td>
</tr>
</tbody>
</table>
chose.

RESULTS
Figure 6 shows the Pareto optimal solutions found by the optimization algorithm. The Pareto optimal solutions clearly show the conflicting nature of the two objectives. The pseudo weight vector has been computed for some of the selected solutions. Table 4 shows the objective values and the impedance controller gains for these solutions. Three solutions were selected from the Pareto optimal set for simulating their performances: the solution that has the best motion tracking \((w = (0,1))\), the solution that has the best force tracking \((w = (1,0))\) and an intermediate solution that has better motion tracking compared to the \((w = (1,0))\) solution (28%) without losing much force tracking (72%). Figure 7 shows the tracking of the hips vertical position for these solutions. Figure 8 also shows the force tracking for these selected solutions. It is seen that as expected the \((w = (0,1))\) solution has a perfect motion tracking however does not produce the required forces. It is also observed that the \((w = (1,0))\) solution deviates from the desired hip trajectory in order to produce the desired force. The \((w = (0.72,0.28))\) solution Tracks the hip trajectory better but in the expense of losing some force tracking. From Tab. 4 it is seen that the best force tracking \((w = (1,0))\) solution has an RMS error of 93 N which is about 12.7% of the hip’s peak load. This solution also has the worst motion tracking with an RMS error of 4.5 cm. The \((w = (0,1))\) solution has a force tracking error of 70% peak load and a motion tracking of 0.06 cm. Therefore the range of force tracking error possible is from 12.7% to 70% peak load with motion tracking error ranging from 4.5 cm to 0.06 cm from which the user can select depending on the test that is being conducted. Figure 9 shows the tracking of the thigh angular position which is controlled by a sliding mode trajectory controller. It is observed that the vertical movement has no effect on the performance of the sliding mode controller. Figure 10 compares the GRF of the selected solutions and the GRF measured in the lab from a human test subject. Since the prosthesis used in this study has a Mauch MicroLite S Knee which cannot be control externally and also a flexible prosthetic foot is attached rigidly to the shank with no ankle joint, we do not expect to have a matching GRF with that of measured from a human test subject.

DISCUSSION
In this study we attempted to take another approach for the design of the control system of a prosthesis test robot in order to make the test robot behave more like a human subject. We recognized that trajectory control although can produce the desired motion it cannot reproduce the forces that are exerted on the prosthesis during a test with a human subject. Therefore impedance control was utilized to perform force tracking in addition to motion tracking. Also the desired force and motion trajectories were derived from human motion test data. Since motion and force tracking are two conflicting objectives that the impedance controller should satisfy, the problem of designing the controller was formulated as an multi-objective optimization problem. In the next step the MOIWO algorithm was used to solve this problem and derive the Pareto optimal solutions. The optimization algorithm was run many times with different parameters to ensure its convergence to the Pareto optimal set. Furthermore the pseudo weight vector approach was used to facilitate the user in selecting a single desired solution from the Pareto set. Simulating the results showed the solutions that were designed for motion tracking performed motion tracking perfectly
Table 4. OBJECTIVE VALUES AND IMPEDANCE CONTROLLER GAINS FOR SELECTED SOLUTIONS

<table>
<thead>
<tr>
<th>pseudo weight force tracking RMS error (KN)</th>
<th>motion tracking RMS error (m)</th>
<th>$C_m$</th>
<th>$K_f$</th>
<th>$K_m$</th>
<th>$M_m$</th>
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<td>0.1138</td>
</tr>
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</table>

Figure 8. VERTICAL COMPONENT OF HIP FORCE FOR SELECTED SOLUTIONS

Figure 9. THIGH ANGULAR POSITION FOR SELECTED SOLUTIONS

but failed to reproduce the desired forces. On the other hand the solution that was designed for force tracking deviated from the desired motion in order to produce the desired force. Also an intermediate solution was found that comes very close to producing the desired forces, with only minor deviations from the desired motion. The proposed approach provides a better means for testing the leg prosthesis by making the test robot capable of reproducing a desired force trajectory. Also, tracking the force on the hip is a more suitable than tracking the GRF since the GRF is the result of the prosthesis’s dynamic response to input from the person wearing the prosthesis and therefore is dependent on the properties of the prosthesis itself. For example in our case the fact that the knee and ankle joint of the prosthesis used were not actively controlled had a great effect on the GRF produced by the prosthesis. Finally using a multi-objective optimization approach for designing the impedance controller gives the user the ability to choose the required amount of force or motion tracking as needed. In terms of future work we intend to implement the designed impedance controller on the robotic platform. Since the impedance controller designed requires the exact knowledge of plant parameters which is not available in practical situations we have to implement the impedance controller as robust con-
controller capable of tolerating errors in system parameters. Also in this study the impedance controller had the objective of tracking force and motion trajectories of able bodied human gait data which we intend to replace with gait data of a person wearing a prosthesis in our future work.

REFERENCES


