Real-time Implementation of Physically Consistent Identification of Human Body Segments

Ko Ayusawa, Gentiane Venture and Yoshihiko Nakamura

Abstract—The mass parameters of the human body segments are important when studying motion dynamics and the in-vivo method to obtain accurate parameters is required in biomechanics studies and for some medical applications. In our previous works, we proposed the method to identify inertial parameters of human body segments in real-time during measurement of motion. However, some obtained parameters are not physically consistent; some masses are negative and inertia tensor matrices are not positive definite. These parameters generate problems in the analysis and the simulation requiring physical consistency. In this paper, we propose the real-time identification method considering physical consistency.

I. INTRODUCTION

The measurement of the mass properties of human body segments has an important role to estimate the internal forces generated inside the body. For the analysis of dynamic motions with high acceleration and angular velocity or that of the difference of individual variability of subjects, high accuracy of measurement of mass parameters is required. On the other hand, non-invasive and simple technique becomes considerably important if monitoring the daily variations of the mass properties. It is difficult to strike a balance between accuracy and convenience. It depends on the purpose of the measurements and many techniques to measure mass properties are developed. Using portable measurement equipments, the whole-body center of mass (COM) can be estimated without pain and difficulty [1]. Interpolations using an approximated human geometry model or literature data can roughly estimate mass properties including inertia tensor [2], [3]. 3D imaging such like CT-scan or MRI and 3D modeling interpolation can provide more accurate mass properties [4], [5], although it takes time and cost and repetitive use presents a danger to health. For the purpose to analyze the dynamics of human motion and the daily variations of human body, the techniques shown above are not adequate and there is a need to develop a method to identify all the segment mass properties of individuals non-invasively.

Based on the robotics identification methods of inertial parameters [6], [7], we have proposed the identification methods of the mass properties of human body segments [8]. The method can identify mass, COM and inertia tensor of each body segment from a short-time measurement using a motion capture system and force-plates. Its low computational cost can realize real-time identification during measurement, which can make a subject specify the body part yet to be identified and enhance the performances of identification. However, the method drawback is that the obtained results are not necessarily physically feasible; there can exist negative masses and non-positive definite inertia matrices, which generate problems in the dynamics simulation and analysis requiring physical consistency. Because it is based on the least squares method and cannot guarantee the physical consistency under measurement noise and modeling error [9]. In addition, the method also estimates the parameters that can be identified not from dynamics but from geometry, so the results are not necessarily physically consistent. In our previous works, we developed the identification of robot dynamics considering physical consistency [10]. The method approximates the rigid body by finite mass points as shown in Fig.1, and represents physically consistent conditions by positivity of mass of each points. Based on the method, in this paper we present an implementation approach for real-time identification of the physically consistent mass properties of human body segments.

II. IDENTIFICATION CONSIDERING PHYSICAL CONSISTENCY AND COMPUTATIONAL STABILITY

The equations of motion of multi-body systems can be written in a linear form with respect to the dynamic parameters [6], [7]. The equations of the multi-body system, composed of $N_L$ rigid bodies and that has $N_J$ degrees of
freedom (DOF), is given by Eq.(1).
\[ Y\phi = f \]  
where,
- \( f \in \mathbb{R}^{NJ} \) is the vector of joint torques including external forces exerted to the system,
- \( \phi \in \mathbb{R}^{10NL} \) is the vector of constant inertial parameters of the system, such that
\[ \phi = \begin{bmatrix} \phi_0^T & \phi_1^T & \cdots & \phi_{n-1}^T \end{bmatrix}^T \]  
- \( \phi_j \in \mathbb{R}^{10} \) is the vector of constant ten inertial parameters of link \( j \); mass \( m_j \), center of mass \( s_j \in \mathbb{R}^3 \), and the inertia tensor \( I_j \in \mathbb{R}^{3 \times 3} \), which are expressed in a frame attached to link \( j \),
- \( Y \in \mathbb{R}^{N_{TJ} \times 10NL} \) is the regressor matrix or regressor, which is composed of \( q \), their derivatives \( \dot{q}, \ddot{q} \), and geometric parameters such as length of each link.

The method to obtain \( Y \) is shown in [7].

For the identification process, we have to compute \( Y \) and \( f \) at every sampling time, measuring generalized coordinates, joint torques, and external forces acting on the system. Then, we arrange \( T \) sampled regressors and forces of Eq.(1) at \( t = t_1, t_2, \ldots, t_T \) lengthwise, and compose the large regressor matrix \( Y_{all} \) and the large vector of forces \( f_{all} \) as below.

\[ Y_{all} \phi \triangleq \begin{bmatrix} Y_{t_1} \\ \vdots \\ Y_{t_T} \end{bmatrix} \phi = \begin{bmatrix} f_{t_1} \\ \vdots \\ f_{t_T} \end{bmatrix} \triangleq f_{all} \]  

If we consider the physical consistency of the identified parameters, all the inertial parameters of each link have to satisfy the following physically consistent conditions.

\[ m_i > 0, \ I_{C_i} > 0 \]  

\( I_{C_j} (= I_j - m_j[s_j \times (s_j \times s_j)]^T) \) is the moment of inertia matrix about the center of mass \( s_j \) expressed in the frame attached to link \( j \). Although the inertial parameters can be generally identified from Eq.(1) by the least squares method, the obtained result from the least squares method is not necessarily physically consistent because of measurement noise and modeling error [9], [11].

In the case of identification of large-DOF systems such as legged systems, they require the large-scale non-linear optimization. In our previous works, we propose the identification method to realize both physical consistency and computational stability for large-DOF systems like legged systems [10]. In this method, we place a finite number of mass points in the convex hull of the link object as shown in Fig.1, and approximate the rigid body by finite mass points in order to replace Eq.(4) with linear inequalities. Here, we can approximate the parameters \( \phi_i \) of the link \( i \) using mass points as follows.

\[ \phi_i = P_i \rho_i \]  

where,
- \( N_{p,i} \) is the number of the mass points located on the link \( i \),
- \( \rho_i \in \mathbb{R}^{N_{p,i}} \) is the vector of mass of all points of link \( j \), \( P_i \in \mathbb{R}^{10 \times N_{p,i}} \) is the matrix to compose \( \phi_i \) of \( \rho_i \). The value of \( P_i \) is related to the position of the mass points, and the points have to be located so that \( P_i \) is of full row rank.

Then, Eq.(4) can be approximated as \( \rho_i > 0_{N_{p,i}} \), where, \( 0_{N_{p,i}} \) is the zero vector with \( N_{p,i} \) elements.

In the 10 dimensional space of inertial parameters, the set of \( \phi_i \) satisfying Eq.(4) exists inside a given convex cone shown in Fig.1. On the other hand, the set of \( \phi_i \) satisfying \( \rho_i > 0_{N_{p,i}} \) corresponds to the polyhedral convex cone inscribed in the cone of Eq.(4). Thus, if \( \rho_i > 0_{N_{p,i}} \) is also verified, then Eq.(4) is verified. Each ridge line means the boundary condition of \( \rho_i > 0_{N_{p,i}} \). If the number of mass points increases, the polyhedral convex cone comes closer to the original cone, and Eq.(4) will be well approximated. \( \rho_i > 0_{N_{p,i}} \) also satisfies other properties of inertial parameters essentially, for example, concerning center of mass; the center of mass of each link always exists in the convex hull of the link.

The vector of all the inertial parameters \( \phi \) can also be represented using all \( N_{p} (= \sum_{i} N_{p,i}) \) mass points as follows.

\[ \phi = P \rho \]  

where, \( P \in \mathbb{R}^{10NL \times N_{p}} \) and \( \rho \in \mathbb{R}^{N_{p}} \) are the following matrix and vector.

\[ P \triangleq \begin{bmatrix} P_1 & \cdots & O \\ \vdots & \ddots & \vdots \\ O & \cdots & P_{NL} \end{bmatrix}, \quad \rho \triangleq \begin{bmatrix} \rho_1 \\ \vdots \\ \rho_{NL} \end{bmatrix} \]  

We can sum up \( \rho_i > 0_{N_{p,i}} \) of all links with the following inequality.

\[ \rho > 0_{N_{p}} \]  

Under the constraint Eq.(8), we solve the optimization problem to minimize the value of the following evaluation function.

\[ f(\rho) = (Y_{all} P \rho - f_{all})^T W_f (Y_{all} P \rho - f_{all}) + (P \rho - \phi^ref)^T N W_\phi N (P \rho - \phi^ref) + \lambda_\rho \rho^T \rho \]  

where,
- \( \lambda_\rho \in \mathbb{R} \) is the positive scaling factor of third term of the function,
- \( W_f \in \mathbb{R}^{N_{TJ} \times N_{TJ}} \) and \( W_\phi \in \mathbb{R}^{10NL \times 10NL} \) are the weight matrices concerning the generalized forces and all the standard inertial parameters respectively, and are positive definite.
- \( \phi^ref \in \mathbb{R}^{N_{p}} \) is the desired value of \( \rho \) in the optimization. \( \phi^ref \) can be obtained from CAD data in the case of robots, and from literature data or measured geometric parameters in the case of humans [8].
- \( N \in \mathbb{R}^{10NL \times 10NL} \) is the matrix representing the null-space of the matrix to compose the base parameters [8].

The solution from the standard dynamics identification minimizes only the first term of Eq.(9). The second term of Eq.(9) is the error from the a priori parameters \( \phi^ref \).
obtained from geometric model. The third term makes the Hessian matrix of the evaluation function positive definite, and realizes computational stability.

We add explanations about the second term of Eq.(9). In usual identification process, only the minimal set of inertial parameters that describes the dynamics of the system can be identified from Eq.(3). This minimal set is called base parameters [12]. Base parameters are too complicated terms to be comprehended naturally to provide a physical meaning. Meanwhile, the second term makes it possible to estimate the standard inertial parameters by utilizing the a priori parameters $\phi^{ref}$.

III. REAL-TIME IDENTIFICATION OF INERTIAL PARAMETERS CONSIDERING PHYSICAL CONSISTENCY

The technique to identify the inertial parameters in real-time is important for the adaptive control of robots. In the case of analysis of human mass properties, this technique is also useful for the generation of persistent exciting trajectories [8]. However, it is difficult to implement the usual method considering physical consistency for real-time identification without modification. Because the quadratic programming under inequality constraints requires more computational cost than the least squares method used for the standard identification. On the other hand, some features of the identification problem using the proposed method have the following advantages in the optimization.

1) The vector $\phi$ and $\rho$ are not time varying and can be treated as constant vectors. It leads that the solution of the optimization is expected to be constant after collecting enough data used for identification. For implementation of real-time identification, we can solve the problem sequentially and reduce the computational cost at each time step.

2) The linear inequality constraints Eq.(8) are simple ones that only give the lower limit of each parameter. In the optimization procedure, it is required to check the active constraints, which makes the process easy.

3) The largest matrix $P$ appearing in Eq.(9) is the block diagonal matrix shown in Eq.(7). It is also required to compute the gradient of the evaluation function for optimization, and the sparseness of $P$ reduces the computational cost.

In this paper, we implement the quadratic programming by the conjugate projected gradient method shown in [13]. The merit of the conjugate gradient method is that it requires relatively little memory and low computational cost at each iteration of optimization, so it is useful when identifying the parameters sequentially. In this section, we discuss the practical implementation method based on the advantageous features mentioned above.

At each time step, we limit the number of iterative computation and solve the quadratic programming. $n_k$ is defined as the number of iteration at each time step, and the $k$-th process of iterative computation at time $t$ is as follows.

\begin{equation}
\rho_{t,k+\frac{1}{2}} = \rho_{t,k} + \frac{p_{t,k}}{p_{t,k}^T A_t p_{t,k}} p_{t,k}^T r_{t,k} \tag{10}
\end{equation}

\begin{equation}
\rho_{t,k+1} = \text{proj} \left( \rho_{t,k+\frac{1}{2}} ; C_{t} \left( \rho_{t,k+\frac{1}{2}} ; r_{t,k+1} \right) \right) \tag{11}
\end{equation}

\begin{equation}
r_{t,k+1} = -(A_t \rho_{t,k+1} + b_t) \tag{12}
\end{equation}

\begin{equation}
w_{t,k+1} = \text{proj} \left( r_{t,k+1} ; C_v \left( \rho_{t,k+\frac{1}{2}} , r_{t,k+1} \right) \right) \tag{13}
\end{equation}

\begin{equation}
z_{t,k+1} = \text{proj} \left( p_{t,k} ; C_v \left( \rho_{t,k+\frac{1}{2}} , r_{t,k+1} \right) \right) \tag{14}
\end{equation}

\begin{equation}
p_{t,k+1} = w_{t,k+1} - \rho_{t,k} A_t w_{t,k+1} \tag{15}
\end{equation}

where, $\rho_{t,k}$ is the solution of the $k$-th process of computation at $t$, $r_{t,k}$, $p_{t,k}$, $w_{t,k}$, $z_{t,k} \in R_{N_r}^r$, are the gradient vectors used for optimization. $A_t, k \in R_{N_r \times N_r}$ are the gradient vectors.

The function $\text{proj}$ shown in Eq.(11), (13), (14) projects the argument vector on the active constraint planes. Using the constraint Eq.(8), Eq.(11), (13), (14) can be simply represented as follows.

\begin{equation}
l_{\rho_{t,k+1}} = \begin{cases} 
\epsilon & \left( l_{\rho_{t,k+\frac{1}{2}} < \epsilon \right) \\
(\rho_{t,k+1} + \epsilon) & \left( \text{else} \right) 
\end{cases} \tag{20}
\end{equation}

\begin{equation}
l_{w_{t,k+1}} = \begin{cases} 
0 & \left( l_{\rho_{t,k+\frac{1}{2}} < \epsilon \wedge l_{r_{t,k+1}} < 0 \right) \\
\left( w_{t,k+1} + \epsilon \right) & \left( \text{else} \right) 
\end{cases} \tag{21}
\end{equation}

\begin{equation}
l_{z_{t,k+1}} = \begin{cases} 
0 & \left( l_{\rho_{t,k+\frac{1}{2}} < \epsilon \wedge l_{r_{t,k+1}} < 0 \right) \\
\left( z_{t,k+1} + \epsilon \right) & \left( \text{else} \right) 
\end{cases} \tag{22}
\end{equation}

where, $l_{\rho_{t,k}}$, $l_{r_{t,k}}$, $l_{w_{t,k}}$, $l_{z_{t,k}}$ are the $l$-th element of $\rho_{t,k}$, $r_{t,k}$, $w_{t,k}$, $z_{t,k}$ respectively, and $\epsilon$ is a positive real number and small enough.

For computing $\rho_{t,k+1}$, $A_t \rho_{t,k}$ and $b_t$ are required, and the complexity to compute $A_t \rho_{t,k}$ and $b_t$ is usually $O(N_r^2)$. However, $A_t$ and $b_t$ can be decomposed like Eq.(16) and Eq.(18), so the complexity can be reduced to $O(N_p)$ using the sparseness of $P$. Moreover, if the number of mass points is small enough compared with the square of DOF ($N_p << N_L^r$), the complexity is $O(N_r^2)$ since the computation can be computed as a concatenation of the sequential least squares method.

The initial value at $t + 1$ is $\rho_{t+1,1} = \rho_{t,n_{k+1}}$. Although the conjugate gradient is updated as $\rho_{t+1,1} = \rho_{t,n_{k+1}}$, the computation is restarted at regular time intervals as $\rho_{t,1} = \rho_{t,n_{k+1}}$, which avoids the accumulation of error of $\rho_{t}$.

IV. EXPERIMENTAL RESULTS

A. Identification model of human body

In this section, we show identification results of the human mass properties using the proposed method. We consider a
model of the human body made of 34 DOF and 15 rigid links [14]: upper torso, lower torso, head, upper arms, lower arms, hands, thighs, shanks, and feet. The waist, the neck, the shoulders, the wrists, the hip joints and the ankles are modeled with spherical joints, and the elbows and the knees are modeled with rotational joints. It represents the most important DOF that are used in daily activities such as locomotion, grasping. In this paper, we use the identification model for legged systems [15]. The equations of motion of legged systems are given by Eq.(23). Eq.(23) is represented as a minimal identification model.

\[
\begin{bmatrix}
Y_{BO} \\
Y_{BC}
\end{bmatrix}
\phi_B = \begin{bmatrix}
0 \\
\tau_c
\end{bmatrix} + \begin{bmatrix}
f_0^{ext} \\
f_c^{ext}
\end{bmatrix}
\tag{23}
\]

where,

- The upper part of Eq.(23) represents the equations of motion of the base-link, which means the root of the kinematic tree structure, and the lower part represents the equations of motion of the joints.
- \(Y_{BO} \in \mathbb{R}^{6 \times N_B}\) is the regressor matrix of the base-link, and \(Y_{BC} \in \mathbb{R}^{(N_j-6) \times N_B}\) is the regressor of the joints,
- \(\tau_c \in \mathbb{R}^{N_j-6}\) is the vector of joint torque,
- \(f_0^{ext} \in \mathbb{R}^6\) is the vector of total external forces exerted to the base-link, and \(f_c^{ext} \in \mathbb{R}^{N_j-6}\) is the vector of external joint torque.

Most common identification methods use Eq.(23) to identify \(\phi_B\), we have proposed to use only the upper-part of the identification model Eq.(23), i.e. \(Y_{BO}\phi_B = f_0^{ext}\) that are the equations of motion of the base-link. The feature of the base-link is that the generalized force which actuates 6 DOFs of the base-link is always zero, which means that the joint-torque measurement is unnecessary for identification using only equations of motion of the base-link. However, this method stands only if the reduction of the system to these six equations keeps unchanged the number of parameters that are structurally identifiable with the whole system. We have mathematically proven that the reduced system leads to similarly identify the whole set of base parameters [15].

**B. Experimental setup**

In this sub-section, we present the experimental setup and the outline of the application to visualize the identification result using the real-time identification method [8]. The human motions are recorded by a commercial optical motion capture system consisting in 10 cameras (Motion Analysis). The resolution of the capture volume is about 3mm. 35 cyan markers are the links whose parameters are small and uncertain whether identification is completed or not, the red colored links mean the parameters of the link are not identified yet, the green ones the identification is completed, and the cyan ones are the links whose parameters are small and uncertain whether identification is completed or not.

In this sub-section, we present the experimental setup and the outline of the application to visualize the identification result using the real-time identification method [8]. The human motions are recorded by a commercial optical motion capture system consisting in 10 cameras (Motion Analysis). The resolution of the capture volume is about 3mm. 35 reflective optical markers pasted on the body are captured by these cameras every 5ms. These markers are modified Helen Hayes Hospital marker set [16] as shown in Fig.2. They are located at the defined anatomical rigid points to diminish the influence from non-rigid skin and muscle movement to insure accuracy of inverse kinematics computations. We can compute the geometric parameters of each link by measuring the position of markers. The contact forces are measured every 1ms by two force-plates (Kistler), and the capture system and the force-plates are synchronized. The tolerances of each force-plate are ±1.0N of forces and ±0.3Nm of moments, and the drifts are ±0.3N/minute of forces and ±0.1Nm/minute of moments.

The identification process is as follows (Fig.3).

1. The geometric parameters of the body are measured by motion capture, and the geometric shape model of each body segment is created by the measured parameters and the body dimension data-base. The a priori parameters \(\phi^{aj}\) can be estimated from the model.
2. From the motion capture system and force-plates, we identify the base parameters and the standard parameters using the real-time method. The real-time method considering physical consistency shown in the previous section is implemented in this process.
TABLE I

<table>
<thead>
<tr>
<th>Link</th>
<th>L1</th>
<th>L2</th>
<th>L3</th>
<th>L4</th>
<th>L5</th>
<th>L6</th>
</tr>
</thead>
<tbody>
<tr>
<td>m</td>
<td>4.420</td>
<td>17.541</td>
<td>1.442</td>
<td>0.433</td>
<td>4.539</td>
<td>6.843</td>
</tr>
<tr>
<td>s_x</td>
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<td>0.024</td>
<td>0.031</td>
<td>-0.040</td>
<td>0.117</td>
</tr>
<tr>
<td>s_y</td>
<td>-0.043</td>
<td>-0.006</td>
<td>0.050</td>
<td>-0.077</td>
<td>-0.050</td>
<td>-0.028</td>
</tr>
<tr>
<td>s_z</td>
<td>0.002</td>
<td>0.221</td>
<td>0.019</td>
<td>0.001</td>
<td>0.161</td>
<td>-0.002</td>
</tr>
<tr>
<td>I_ee</td>
<td>0.027</td>
<td>0.716</td>
<td>0.013</td>
<td>0.001</td>
<td>0.048</td>
<td>0.025</td>
</tr>
<tr>
<td>I_ey</td>
<td>0.023</td>
<td>0.633</td>
<td>0.002</td>
<td>0.002</td>
<td>0.063</td>
<td>0.086</td>
</tr>
<tr>
<td>I_ez</td>
<td>0.050</td>
<td>0.279</td>
<td>0.011</td>
<td>0.003</td>
<td>0.022</td>
<td>0.089</td>
</tr>
<tr>
<td>I_yy</td>
<td>0.000</td>
<td>-0.013</td>
<td>0.000</td>
<td>0.001</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>I_yz</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>I_zz</td>
<td>0.008</td>
<td>0.006</td>
<td>0.001</td>
<td>0.001</td>
<td>0.002</td>
<td>0.011</td>
</tr>
</tbody>
</table>

3 Using the monitor to display the CG human model whose body segments are colored according to the identification results (Fig.4), the subject can visualize instantly the body segment yet to be identified and improve the quality of identification results.

The detail of the process are shown in [8]. This visualizing system draw the picture of results at 30fps, so all the computation of identification have to be finished until drawing results, although it is the soft real-time system that tolerates deadline miss of visualization. The presented method is implemented on the work station with a Intel Core2 Duo processor (2.60GHz).

We mention the location of mass points used in the proposed method. Eq.(4) will be well approximated if the number of mass points increases, which leads to a large computation cost of the optimization. If we utilize the sparseness of P to reduce the computation cost for the optimization, the cost increases in proportion to the square of the number of mass points. Moreover, there exist the measurement and geometric modeling error in practice, thus the obtained results cannot be improved if we approximate Eq.(4) with maximum accuracy. It means that we should choose the number of points according to the computational feasibility and the practical limit of accuracy improvement. In this instance, we create the bounding box of each link object of the geometric model obtained in the first process shown above, and we put 27 (= 3^3) equally-spaced points in each bounding box.

The other designed parameters are mentioned. The weight matrices W_\phi and W_\tau are the variance-covariance matrices obtained from the estimation errors of \phi^ref and \tau, and we choose \lambda_\rho = 0.001. The initial value of \rho is the vector whose elements are all \epsilon, and the number of iteration is n_k = 2.

C. Results of identification

First, we compared the computation time of the method with that of the sequential least squares method. In this paper, the number of the parameters to be identified is 150 in \phi, and 405 parameters of \rho have to be computed in the optimization process. The computation time of n_k (= 2) iterations was 3.8ms in the least squares method, and 6.7ms in the proposed method. The increase of time was about 2.9ms, however, the delay is within the acceptable range with respect to the frame-rate of the visualization system.

Then, we measured the motion during 3 minutes using the visualization interface, and the standard inertial parameters estimated from the proposed real-time method are given in Table I; Table I shows the mass m/kg, the COM s_i/m, and the components of moment of inertia matrix I_{ij}kgm^2 (around the COM) of some typical links; lower torso(L1), upper torso(L2), right foot(L3), right hand(L4), head(L5), right thigh(L6). And Table II shows the estimated parameters obtained from the least squares type method of [8]. In Table II, all the masses were positive, however most of the principal moments of inertia showed negative values, and they were clearly not physically consistent. On the other hand, all the results in Table I satisfied the conditions of Eq.(4), which means that the proposed method could estimate the standard inertial parameters successfully.

We also compared the results with the parameters computed from the post-processing quadratic programming that continues iterative computations until convergence after the measurement. Table III shows the parameters from the post-processing off-line method. From the tables, the maximum residual errors were 0.002kg of mass, 0.001m of COM, and 0.001kgm^2 of inertia tensor, and they were small enough with respect to the measurement accuracy. Thus, the parameters reached the post-processing solution sufficiently even if we solved the quadratic programming sequentially and limited the number of iteration to n_k = 2 for real-time implementation.

For validation, we attached a 2.0kg weight to the right

TABLE II
STANDARD INERTIAL PARAMETERS OF 6 LINKS ESTIMATED FROM THE LEAST SQUARES METHOD.

<table>
<thead>
<tr>
<th>Link</th>
<th>L1</th>
<th>L2</th>
<th>L3</th>
<th>L4</th>
<th>L5</th>
<th>L6</th>
</tr>
</thead>
<tbody>
<tr>
<td>m</td>
<td>2.676</td>
<td>19.207</td>
<td>1.860</td>
<td>0.509</td>
<td>4.072</td>
<td>5.940</td>
</tr>
<tr>
<td>s_x</td>
<td>0.043</td>
<td>-0.030</td>
<td>-0.036</td>
<td>0.009</td>
<td>-0.062</td>
<td>0.074</td>
</tr>
<tr>
<td>s_y</td>
<td>-0.105</td>
<td>0.001</td>
<td>0.035</td>
<td>-0.005</td>
<td>-0.110</td>
<td>-0.026</td>
</tr>
<tr>
<td>s_z</td>
<td>-0.241</td>
<td>0.222</td>
<td>-0.001</td>
<td>-0.002</td>
<td>0.207</td>
<td>0.001</td>
</tr>
<tr>
<td>I_ee</td>
<td>0.039</td>
<td>0.239</td>
<td>0.002</td>
<td>0.004</td>
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<td>0.020</td>
</tr>
<tr>
<td>I_ey</td>
<td>-0.229</td>
<td>0.234</td>
<td>0.012</td>
<td>0.008</td>
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</tr>
<tr>
<td>I_ez</td>
<td>-0.071</td>
<td>0.090</td>
<td>0.040</td>
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<td>-0.127</td>
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<tr>
<td>I_yy</td>
<td>0.054</td>
<td>-0.014</td>
<td>-0.011</td>
<td>-0.001</td>
<td>-0.138</td>
<td>0.039</td>
</tr>
<tr>
<td>I_yz</td>
<td>-0.068</td>
<td>-0.193</td>
<td>0.003</td>
<td>0.002</td>
<td>-0.216</td>
<td>0.027</td>
</tr>
<tr>
<td>I_zz</td>
<td>0.025</td>
<td>0.020</td>
<td>-0.013</td>
<td>-0.004</td>
<td>0.007</td>
<td>0.001</td>
</tr>
</tbody>
</table>

TABLE III
STANDARD INERTIAL PARAMETERS OF 6 LINKS ESTIMATED FROM THE POST-PROCESSING QUADRATIC PROGRAMMING.

<table>
<thead>
<tr>
<th>Link</th>
<th>L1</th>
<th>L2</th>
<th>L3</th>
<th>L4</th>
<th>L5</th>
<th>L6</th>
</tr>
</thead>
<tbody>
<tr>
<td>m</td>
<td>4.149</td>
<td>17.541</td>
<td>1.441</td>
<td>0.431</td>
<td>4.538</td>
<td>6.843</td>
</tr>
<tr>
<td>s_x</td>
<td>0.019</td>
<td>-0.023</td>
<td>-0.024</td>
<td>0.030</td>
<td>-0.040</td>
<td>0.117</td>
</tr>
<tr>
<td>s_y</td>
<td>-0.044</td>
<td>-0.005</td>
<td>0.051</td>
<td>-0.007</td>
<td>-0.070</td>
<td>-0.028</td>
</tr>
<tr>
<td>s_z</td>
<td>0.002</td>
<td>0.221</td>
<td>0.019</td>
<td>0.002</td>
<td>0.161</td>
<td>-0.002</td>
</tr>
<tr>
<td>I_ee</td>
<td>0.026</td>
<td>0.715</td>
<td>0.013</td>
<td>0.001</td>
<td>0.048</td>
<td>0.035</td>
</tr>
<tr>
<td>I_ey</td>
<td>0.023</td>
<td>0.633</td>
<td>0.002</td>
<td>0.002</td>
<td>0.063</td>
<td>0.086</td>
</tr>
<tr>
<td>I_ez</td>
<td>0.049</td>
<td>0.278</td>
<td>0.011</td>
<td>0.003</td>
<td>0.021</td>
<td>0.026</td>
</tr>
<tr>
<td>I_yy</td>
<td>0.000</td>
<td>-0.014</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>I_yz</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>I_zz</td>
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<td>0.006</td>
<td>-0.001</td>
<td>-0.001</td>
<td>0.002</td>
<td>0.011</td>
</tr>
</tbody>
</table>
hand or the left shank, and identify the new inertial parameters respectively. Then, we compared them with the parameters with no mass and checked whether only the mass of the body part with the weight increased 2.0kg. Fig.5 shows the amount of change of mass of each body part. In Fig.5, the link is proportionally colored in red with the increase in mass, and in blue with the decrease. As seen from Fig.5, the weight attached to the right hand was successfully identified, and the increase of the mass of the right hand was 1.9kg. In the case when the weight was attached to the left shank, though the segment whose mass increases the most was actually the left shank, the increase of the mass of was 1.0kg; on the other hand, the increase of mass of the left foot was the second largest, and was 0.7kg. In that case, it was difficult to detect the increase of 2.0kg only in the left shank, because the weight was attached to the left ankle, to be exact. In both cases, the changes of mass of the other body segments were within ±0.3kg, which are larger than the accuracy of two force-plate: about ±2.0N. In our method, we utilize the a priori parameters obtained from the body dimension database to estimate the none-base parameters; however, in the database, there is no sample such that a 2.0kg weight was attached, which is considered to lead the errors.

V. Conclusion

We have proposed a physically consistent identification method for the inertial parameters of the whole body segments of humans. The parameters can be estimated in real-time from the non-invasive and simple measurement using a motion capture system and force plates, and the obtained results always satisfy physical consistency such as positive definiteness of mass and inertia tensor. In general, physically consistent conditions are represented as non-linear inequality constraints, and the computation for identification is complicated. In this method, we approximate a rigid body by a finite number of mass points and replace the conditions with the positivity of mass of each point, which leads the computational speed and stability. As inertial parameters of a rigid body are not time varying, the solution of identification can be treated as constant ones during measurement. Thus, we can solve the problem sequentially and reduce the computational cost at each time step for real-time procedure. Making use of the sparseness of the regressor matrix of mass points model, we implemented the sequential quadratic programming, and achieved the computational delay of about 6.7ms of each iteration. The delay was enough small for the visualization system [8] used to improve the quality of identification. All the parameters obtained from the real-time method satisfied physical consistency. Compared with the parameters from post-processing off-line identification, the parameters reached the post-processing solution sufficiently even in the real-time process. For validation, we identified the parameters in the case when a 2.0kg weight was attached at different locations on the body. The results were compared with the parameters with no mass, and the body segment equipped with the weight was successfully detected.

REFERENCES