Realtime Identification Software For Human Whole-Body Segment Parameters Using Motion Capture and Its Visualization Interface

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Abstract—The segment parameters of the human body are indispensable to compute the motion dynamics. They are used in numerous medical fields, in biomechanics and rehabilitation. Inaccuracies in the parameters generate errors in the interpretation of the motion analysis. So far no systematic method to estimate them has been proposed, rather parameters are scaled from generic tables or estimated with inappropriate methods for a clinical use. Based on our previous works, we have developed a software and interface that allow to estimate in real-time the whole-body segment parameters, and to visualize the convergence towards the identification results in real time.

I. INTRODUCTION

The inertial parameters of the human body are crucial to study human motions dynamics. They are often used in biomechanics studies, in gait studies and for medical applications as orthopedics, neurology, musculoskeletal disorders studies. This knowledge permits refined diagnosis and personalized health-care. The stability of gait is usually examined from the trajectory of the whole-body center of mass (COM). The computation of the segment parameters (SP): the inertia and the position of the COM of each link of the body, is a key-step in gait analysis and to monitor the variations of muscle mass due to disease, hospitalization, rehabilitation or training. The recent development in portable technologies have allowed developing systems to estimate in-vivo the position of the whole-body COM [1], [2]. Nevertheless, by lack of accurate methodology, the inertias are usually not estimated in-vivo and are rather computed by interpolations of literature data [3], [4]. These data are often obtained by photogrammetry [5], known to be poorly accurate, or more recently by 3D imaging (CT-scan or MRI) and 3D modeling interpolations, known to be expensive (equipment and time-consuming) and hazardous (exposure to radiations) [6], [7]. There is no uniformity neither in the landmarks nor in the model of the human-body used [8]; and with the profusion of references an adequate choice fitting with the population under study is difficult. Moreover, to properly interpolate the available database, massive geometric measurements are necessary. In addition, it is shown in [9] that errors in the body-segment mass-parameter affect significantly the analysis results. Consequently, there is a pressing need to develop reliable and robust methods to estimate in-vivo the SP of the human body.

Based on our previous works about identification of base-parameters of the human body [10], in this paper we present a methodology to perform real-time estimation of the whole-body SP of humans, based on motion and contact force measurements [11], as well as a visualization application that is used to generate persistent exciting trajectories [12]. This method allows in-vivo subject-specific identification of the SP with a fast, safe and robust environment. It makes use of both the identification of the base-parameters and an interpolation from data extracted from the data-base of human body [13].

II. IDENTIFICATION WITH CONTACT FORCE INFORMATION

A. Identification model of humanoids

From [14], [15] and [16], [17], the inverse dynamics can be written in a linear form with respect to the SP as shown in [10]. Thus, by separating the vector of constant inertial parameters, the identification model, i.e. the inverse dynamics written such that the model appears in a linear form with respect to the dynamics parameters, Eq. 1 is obtained.

\[ Y \phi = \left[ Y^O \ Y^C \right] \phi = \left[ 0 \ \tau \right] + \sum_{k=1}^{N_c} \left[ J^O_{ck} \ J^C_{ck} \right] F^\text{ext} \]

where:

- \( \tau \in R^{6J-6} \) is the vector of joint torques,
- \( N_c \) is the number of contact points with the environment,
- \( F^\text{ext} \in R^6 \) is the vector of external forces exerted to the humanoid at contact \( k \),
- \( J_k = [J^O_{ck} \ J^C_{ck}] \in R^{6 \times N_J} \) are the basic Jacobian matrices of the position at contact \( k \) and of the orientation of the contact link with respect to \( q_0 \) and \( q_c \), which are used to map \( F^\text{ext} \) to the vector of generalized forces,
- \( \phi \in R^{10n} \) is the vector of constant inertial parameters,
- \( Y = [Y^O \ Y^C] \in R^{N_J \times 10n} \) is the regressor or regressor, and the function matrix of generalized coordinates \( q_0 \) of the base-link, the joint angles \( q_c \) and their derivatives \( \dot{q}_0, \dot{q}_c, \ddot{q}_0, \ddot{q}_c \), \( Y_0 \in R^{6 \times 10n} \) is the regressor corresponding in the six equations of motion of the base-link, one for each of is degree of freedom (DOF).

Not all the dynamics parameters is necessary to compute the inverse dynamics. Only the minimal set of inertial parameters that describes the dynamics of the system can be identified [18]. This minimal set is called base parameters \( \phi_B \in R^{Nu} \). It is computed symbolically or numerically.
from the vector of SP $\phi$ by eliminating those that have no influence on the model and regrouping some according to the kinematics of the system [19]–[21]. The base parameters $\phi_B \in \mathbb{R}^{N_B}$ can be calculated from the standard parameters $\phi \in \mathbb{R}^{10n}$ as follows:

$$\phi_B = Z\phi$$

(2)

Where, $Z \in \mathbb{R}^{n \times 10n}$ is the composition matrix of base parameters [22].

The minimal identification model given by Eq. 3 is thus obtained. $Y_B \in \mathbb{R}^{N_c \times N_B}$ is called the regressor for the base parameters.

$$Y_B\phi_B = \begin{bmatrix} Y_{OB} \\ Y_{CB} \end{bmatrix} \phi_B = \begin{bmatrix} 0 \\ \tau \end{bmatrix} + \sum_{c=1}^{N_c} \begin{bmatrix} J_{Ob}^T \\ J_{Cb}^T \end{bmatrix} F_{ext}^c$$

(3)

B. Identification of base parameters from contact-forces

Most common identification methods use Eq. 3 and thus require the measurement of:

- the base-link information $q_0$,
- the chains information $q_c$ and $\tau$,
- the external forces $F_{ext}^c$ for the $N_c$ contact points.

However it is difficult to measure accurately the joint torque as it is a function of the muscles force and the joint viscoelastic characteristics. We thus have proposed to perform the identification of $\phi_B$ using only the upper-part of the identification model Eq. 3, the equations of motion of the base-link, and thus to estimate the pure SP [10].

$$Y_{OB}\phi_B = \sum_{c=1}^{N_c} J_{Ob}^T F_{ext}^c$$

(4)

We obtain a system given by Eq. 4 that is not a function of the joint torque $\tau$. Consequently to estimate the set of base parameters $\phi_B$, the measurement of the joint torque for each joint is not required. Only the measurement of the contact forces $F_{ext}^c$ at contact $k$, the joint angles $q_c$, and the generalized coordinates $q_0$ are required. This information can be measured by motion capture and force-plates. In addition, by measuring directly the contact force $F_{ext}^c$, there is no need to discriminate between the phases of double support (both foot on the ground) and single support (only one foot on the ground).

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. This has been demonstrated mathematically in [22]; thus the structural identifiability of the base parameters is maintained and Eq. 4 leads to similarly identify the whole set of base parameters.

An estimate of the vector of base parameters $\hat{\phi}_B$ is thus obtained by solving Eq. 4 with the least square method.

C. Estimation of whole-body segment parameters

As mentioned above, only the base parameters $\phi_B$ can be identified from the identification model. The base parameters $\phi_B$ include the necessary and sufficient information to construct the equations of motion. However, the base parameters are computed by eliminating and regrouping the standard parameters $\phi$ according to the kinematics, so they are too complicated terms to be comprehended straightforwardly and to give a sufficient physiological meaning. Therefore, especially to measure the parameters of human body and to apply to medical fields, the standard SP $\phi$ are more comprehensible than the base parameters $\phi_B$.

However after identification of the base parameters $\hat{\phi}_B$ as shown in section II-B it is possible to compute the standard parameters $\phi$ from literature data or data-base [3], [23], we thus can obtain the whole set of SP with certainty. The estimated standard parameters meet the identification results (base-parameters) without distortion, and minimize the error of preliminary information from data-base.

For the linear equation (2), the general form of the least-squares solution for a rank-deficient regressor is given by [24]:

$$\phi = Z^#\phi_B + (E - Z^#Z)z$$

(5)

where $z \in \mathbb{R}^{10n}$ is an arbitrary vector, and $E$ is the identity matrix. When using the identified base parameters $\hat{\phi}_B$, the main problem resides in determining the vector $z$ projected to the null space of the composition matrix $Z$.

We choose the vector $z = \phi^{ref}$, where $\phi^{ref}$ is the information found in the data-base for the standard parameters or reference standard parameters, and finally the subject-specific standard parameters $\phi$ can be obtained as follow:

$$\phi = Z^#\hat{\phi}_B + (E - Z^#Z)\phi^{ref}$$

$$= \phi^{ref} + Z^#(\hat{\phi}_B - \phi^{ref})$$

(6)

Where, $\phi^{ref} = Z\phi^{ref}$.

Eq. 6 satisfies Eq. 2. Eq. 6 also implies that $\phi$ minimizes $||\phi - \phi^{ref}||$, which means the error of the reference standard parameters $\phi^{ref}$.

III. REAL-TIME VISUALIZATION OF IDENTIFIABILITY

A. Outline

In this section, we present the outline of the application to visualize the identification result using the real-time identification method. Each step is then detailed in the following subsections. The human motions are recorded every $5$[ms] by a commercial optical motion capture system consisting in $10$ cameras (Motion Analysis) and $35$ reflective optical markers, and the contact forces are measured every $1$[ms].
by the force-plates (Kistler) (Fig. 1). The model of human consists in 34 DOF [10]. The motion-data and the force-data are synchronized. The identification process is as follows (Fig. 2):

1) the geometric model of human is defined, measure the geometric parameters of the model from motion capture, and estimate the prior standard inertial parameters from geometric parameters and data-base of human body.

2) From the motion capture and force-plates, we identify the base parameters and the standard parameters using the real-time method.

3) Using colored presentation to specify the links yet not to be identified, we can improve the quality of identification results.

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**B. The measurement of geometric model and the prior estimation of standard inertial parameters**

To obtain good results it is important to define the kinematic model used to describe the human body, and to obtain its characteristic geometric parameters. As discussed in our previous work, the modeling depends on the purpose of identification and the real constraints such as the measure- ment facility [10]. We consider a model of the human body consisting in 34 DOF and 15 rigid links as described in Table I. It represents the most important DOF that are used in daily activities such as locomotion. DOF can be added and removed according to the needs, keeping in mind that a compromise is necessary between the number of DOF and the identifiability (smallness of parameters if too numerous, excitation more difficult) of the SP.

The geometric parameters of human need to be measured. Usually they would be measured manually, here we use an automatic method making use of the optical marker positions as shown in Fig. 1. These markers are located at the defined anatomical points to insure accuracy of inverse kinematics computations, thus we can automatically compute the geometric parameters of each link by measuring the relative position of markers.

Then, the standard inertial parameters are estimated from the obtained geometric model. In this paper, we apply the method described in [13] and that makes use of the data-base of the human body available from [23], to estimate the standard inertial parameters of the human body. The data-base consists in the 49 diagnostic measurement items and the total body mass of 308 Japanese people. The prior estimation of the standard parameters is performed as follows: First we measure some of the 50 items (from marker positions and force-plates) to use as the input of the estimation routine, and then we compute the other items using a linear regression. Second, the geometric shape of the human body is modeled as shown in Fig. 3. In this model, each link of the human body is approximated by simple primitive shapes. For example, oval sphere, truncated cone, and boxes. Then, the size and volume of each primitive is computed from the 49 measurement items, and the inertial parameters are obtained, assuming that the density of each link is uniform. The results presented in Fig. 3 are obtained for 3 male subjects, from left to right the body height and weight are: 1.73m 58Kg, 1.62m 54Kg and 1.76m 76.3Kg. The differences in body shape are clearly visible from the obtained model.

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**C. On-line identification of the base parameters**

From the inverse kinematics computations of marker positions, the generalized coordinates and their derivatives are obtained, and the regressor in Eq. 4 is calculated. The total external force exerted to the frame of the base-link is calculated from the force-plates data as shown in Eq. 4.

After sampling along an motion, the vector of base parameters \( \phi_B \) is estimated by solving the obtained system of Eq. 4 using the linear least squares method. [25] To guaranty real time identification the regressor and the vector

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**TABLE I**

**CHosen DOF in the model of the human body**

<table>
<thead>
<tr>
<th>name of joint</th>
<th>type of joint</th>
<th>number of DOF</th>
</tr>
</thead>
<tbody>
<tr>
<td>neck</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>waist</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>right shoulder</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>right elbow</td>
<td>revolute</td>
<td>1</td>
</tr>
<tr>
<td>right wrist</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>left shoulder</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>left elbow</td>
<td>revolute</td>
<td>1</td>
</tr>
<tr>
<td>left wrist</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>right hip</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>right knee</td>
<td>revolute</td>
<td>1</td>
</tr>
<tr>
<td>right ankle</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>left hip</td>
<td>spherical</td>
<td>3</td>
</tr>
<tr>
<td>left knee</td>
<td>revolute</td>
<td>1</td>
</tr>
<tr>
<td>left ankle</td>
<td>spherical</td>
<td>3</td>
</tr>
</tbody>
</table>

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Fig. 3. The geometrically approximate shape of human in 3 different cases
of external forces are sub-sampled if needed; the computation speed can thus be adjusted to the computer performances. For real-time computation, the on-line least squares algorithm is implemented, however with this method an initial value for $\hat{\phi}_{B0}$ is necessary. Actually, the forces and moments of the 6-axis external force in Eq. 4 have different physical unit, and different measurement accuracy. To avoid discrepancies in the results the weighted least squares method is used, attributing a different weight to the 6 components. In addition, when dealing with time-varying parameters, as it can be the case when human handles or releases objects during the measurements, an exponential forgetting coefficient $\lambda_n$ is used. The preceding features are implemented as follow: At times $t = [1, n]$, the estimated parameters $\hat{\phi}_{B,n}$ at $t = n$ is computed from $\phi_{B,n-1}$ at $t = n - 1$ as follow.

$$\hat{\phi}_{B,n} = \lambda_n \hat{\phi}_{B,n-1} + K_n (F_n - Y_{OB,n} \hat{\phi}_{B,n-1})$$ (7)

Where,

- $\lambda_n (0 \leq \lambda_n \leq 1)$ is the time-varying forgetting factor.
- $Y_{OB,n}$ and $F_n$ are the regressor and the external force in Eq. 4 at the time $t = n$.
- $K_n \in R^{N \times N_n}$ is the gain matrix as follow:

$$K_n = P_{n-1} Y_{OB,n}^T V_n^{-1}$$ (8)

- $V_n \in R^{p \times 6}$ is defined as follow:

$$V_n = \lambda_n \Sigma_n + Y_w t P_{n-1} Y_w T$$ (9)

- $P_n \in R^{N \times N_n}$ is defined by defined by:

$$P_n = \sum_{i=1}^{n} (Y_{OB,i}^T \Sigma_i Y_{OB,i})^{-1}$$ (10)

And the on-line inverse matrix calculation is given by:

$$P_n = \frac{1}{\lambda_n} (P_{n-1} - P_{n-1} Y_{OB,n}^T V_n^{-1} Y_{OB,n} P_{n-1})$$ (11)

- $\Sigma_n \in R^{p \times 6}$ is the weighted matrix.

The weighted matrix $\Sigma_n$ is chosen as the covariance matrix for the disturbance of $F$. We consider that the 6 axis elements of $F$ are independent and thus $\Sigma_n$ is diagonal. The i-th diagonal element $\sigma_{i,n}^2 (1 \leq i \leq 6)$ is the variance of the estimated error of each component of $F$. $\sigma_{i,n}$ can be calculated using $A_{i,n} \in R^{N \times N_n}$, $b_{i,n} \in R^{N_n}$, $c_{i,n} \in R$, $d_n \in R$ as follow, where $f_{i,n} \in R$, $y_{i,n} \in R^{N \times N_n} (1 \leq i \leq 6)$ are the each component of respectively $F_n$ and $Y_{OB,n}$.

$$\sigma_{i,n}^2 = \frac{1}{d_n} (\phi_{B,n-1}^T A_{i,n} \phi_{B,n-1} - 2 \phi_{B,n}^T b_{i,n} + c_{i,n})$$ (12)

$$A_{i,n} = y_{i,n}^T y_{i,n} + \lambda_n^2 A_{i,n-1}$$ (13)

$$b_{i,n} = f_{i,n} y_{i,n} + \lambda_n^2 b_{i,n-1}$$ (14)

$$c_{i,n} = f_{i,n}^2 + \lambda_n^2 c_{i,n-1}$$ (15)

$$d_n = 1 + \lambda_n d_{n-1}$$ (16)

From Eq. 7, Eq. 11, and Eq. 12 - (16), we can compute $W_n$, $P_n$, and $\phi_{B,n}$ every time, and also obtain $\phi_{n}$ from Eq. (10) using $\Sigma_n$. The initial value for $P_0$, $\hat{\phi}_{B0}$ and $\phi_0$ can be chosen as a-priori knowledge. If they are unknown, we choose $\hat{\phi}_{B0} = 0$, $\phi_0 = 0$ and $P_0 = \gamma E$. Similarly, $A_{i,0}$, $b_{i,0}$, $c_{i,0}$, $d_{i,0}$ are chosen as zeros without a-priori data. A large value of $\gamma (> 0)$ leads to a fast convergence of the identification procedure, nevertheless $P_n$ becomes unstable without enough exciting motion data. The forgetting factor $\lambda_n$ is often chosen with a constant value from 0.995 to 1. If the parameters are constant (no object carried) $\lambda = 1$ is chosen (no forgetting); furthermore if the parameters are bound to changes (when handling and releasing objects) we chose $\lambda < 1$.

D. Visualization of Persistent Excitation Trajectory

The accuracy of the identified base parameters depends in the motion used to sample the identification model. It is important to sample the identification model along a motion that excites the dynamics to estimate. Such motions are called Persistent Exciting Trajectories [12]. A criterion to define an appropriate motion is to consider motion leading to small value of the condition number of the obtained regressor. However, a large number of DOF and time-varying contact situation complicate the definition of persistent exciting trajectories [26].

We propose to make use of the real-time identification to visualize the identification as well as adjust the persistent exciting movements. During the measurement, using a representation of the identified link parameters and not yet identified link parameters allow to intuitively specify which links need to be excited. The examinee gets the feedback and can generate the adequate persistent exciting trajectories in order to improve the identification results.

The relative standard deviations computed for each parameter [12], [27] are a statistical indicator of the identification results quality. Considering that the regressor $Y_{OB}$ of the linear system Eq. 4 is a deterministic one, and the modeling error $\rho = F - Y_{OB} \hat{\phi}_B$ is a zero mean Gaussian noise, the covariance matrix $C_n \in R^{N \times N}$ of the estimation error of $\hat{\phi}_B$, are computed as follow:

$$C_n = E((\phi_B - \hat{\phi}_{B,n})(\phi_B - \hat{\phi}_{B,n})^T) = P_n$$ (17)

where $E$ is the expectation operator. Eq. 7, Eq. 8, and Eq. 11 of the on-line least squares algorithm are similar to equations of a Kalman filter without the system noise, and $P_n$ is equivalent to the covariance matrix of $C_n$.

$c_{n,(i,i)}$ is the diagonal elements of $C_n$, and the relative standard deviation $\sigma_{\phi_i,n}$ is thus computed as follow:

$$\sigma_{\phi_i,n}% = 100 \sqrt{\frac{c_{n,(i,i)}}{\hat{\phi}_{B_j,n}}}$$ (18)

We consider that a parameter with a relative standard deviation $\sigma_{\phi_i,n}%$ lower than a specified threshold is well identified, keeping in mind that this is only an indicator based on statistical assumptions. However for parameters with small values, they may be well identified although $\sigma_{\phi_i,n}%$ is large.

The results are visualized in an active interface using the 3D representation of the human figure defined in section
Each link color is changing and defined according to a simple rule as follow: $n_{Bj}$ is the number of the base parameters of the link $j$, $n_{Bj,G}$ is the number of parameters that $\sigma_{ij}$ is lower than 10\% and $n_{Bj,B}$ is the number of parameters that $\sigma_{ij}$ is not lower than 10\% but small parameters($<0.02$), and $n_{Bj,R} = n_{Bj} - n_{Bj,G} - n_{Bj,B}$. Then rgb color values of each link are chosen as ratio of $n_{Bj,R}$, $n_{Bj,G}$, and $n_{Bj,B}$. Starting from red for non identified parameters to green for fully identified parameters.

IV. EXPERIMENTAL RESULTS

We propose to compare the results obtained with the standard off-line identification procedure and the optimal identification procedure featuring the visualization. For that we record motions that are known to be persistent exciting trajectories and have proven to allow identifying the whole body base-parameters [26]. In addition we record three motions using the real-time visualization interface. During this phase the motions are free and only adjusted to provided the identification of the parameters based on the color changes. The initial conditions for real-time identification are $\lambda_0 = 1.0$, $\gamma = 0.001$, and other parameters are zeros.

The results obtained for 3 motions are given in Table II. The condition number of the regressor $\text{cond}(\mathbf{Y}_{OB})$ and the length of data of each motion are shown here. And the number of estimated parameters $n_{est} = n_{Bj,G} + n_{Bj,B}$ is also shown. Usually randomly chosen motions of the whole body lead to regressor of high condition number about 500; in our previous works, we realized condition number about 50 using the combination of several motions from a gymnastic TV program [26]. Table II shows that using the interface lead to obtain condition numbers of about 30. And thus to enhance the excitation properties of the recorded motions by visual feedback and the quality of the estimation.

<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>2.79</td>
<td>19.38</td>
<td>1.94</td>
<td>0.43</td>
<td>3.91</td>
<td>6.01</td>
</tr>
<tr>
<td>$Cx$</td>
<td>-0.04</td>
<td>-0.03</td>
<td>-0.03</td>
<td>-0.01</td>
<td>-0.05</td>
<td>0.08</td>
</tr>
<tr>
<td>$Cy$</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>-0.01</td>
<td>-0.12</td>
<td>-0.02</td>
</tr>
<tr>
<td>$Cz$</td>
<td>0.01</td>
<td>0.21</td>
<td>-0.03</td>
<td>-0.06</td>
<td>0.40</td>
<td>0.02</td>
</tr>
<tr>
<td>$J_{xx}$</td>
<td>0.46</td>
<td>0.62</td>
<td>0.02</td>
<td>0.01</td>
<td>0.32</td>
<td>0.04</td>
</tr>
<tr>
<td>$J_{yy}$</td>
<td>0.03</td>
<td>0.71</td>
<td>0.03</td>
<td>0.01</td>
<td>0.01</td>
<td>-0.08</td>
</tr>
<tr>
<td>$J_{zz}$</td>
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<td>0.01</td>
<td>0.07</td>
<td>0.01</td>
<td>-0.09</td>
<td>-0.15</td>
</tr>
<tr>
<td>$J_{yz}$</td>
<td>0.01</td>
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<td>-0.02</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
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<tr>
<td>$J_{zx}$</td>
<td>-0.07</td>
<td>-0.06</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.09</td>
<td>0.02</td>
</tr>
<tr>
<td>$J_{xy}$</td>
<td>-0.07</td>
<td>-0.02</td>
<td>-0.01</td>
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<td>0.01</td>
<td>0.00</td>
</tr>
</tbody>
</table>

V. CONCLUSION

In this paper we have shown that:
- It is possible to estimate all the standard inertial parameters with a systematic and fast method. This method makes use of 1. the identification of the base parameters and 2. the prior estimated parameters extracted from the data-base of human body. The estimated parameters...
meet the identification results without distortion, and minimize the error of prior information from data-base.
- The proposed approach of real-time identification and visualization of identification results during measurement allows to generate persistent exciting trajectories.
- The real-time visualization interface improved the excitation properties of a data-set by visual feedback of the requested excitation.

However some of the obtained results have shown physically incorrect estimation of the standard parameters. To fix this issue the method requires a more complete data-base for a-priori parameters and to set some the dynamics constraints of center of mass and inertia. An other direction to investigate in future works is the replacement of the motion capture system by stereovision based motion capture for example.

REFERENCES


