Identification of human body dynamics for evaluating assistive devices

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***Abstract*— Human assistive devices are expected to support daily life in several nations, and are studied and developed intensively. In order to promote the industrial expansion in this field, the quantitative evaluation about their effect on humans will have a great role. Though human motion capturing can estimate the joint trajectories and torques of each person when using a device, the measurement or estimation of his/her subject-specific parameters is essential for the accurate evaluation. This paper presents our work about the identification of whole-body geometric and inertial parameters by using motion capture system and force plates.**

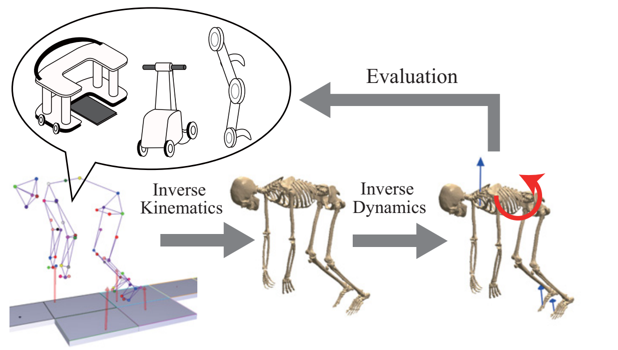

Fig. 1. Flow of the human motion analysis by using motion capture.

I. Introduction

Recent development of human assistive devices have been gathering attention in several nations entering the super-aged society. They are expected to support both the daily life of elderly people and to relieve the burden on nursing-care workers. However, the difficulty of evaluation often leads the slow development and implementation of the devices. The reliable evaluation framework of the devices, especially for the assistive performance on human body, needs to be developed for industrial growth, and has recently been studied and investigated [1], [2].

Human motion capturing also has an important role to estimate human joint trajectories and torques during when using an assistive device. Inverse kinematics and dynamics analysis of human motion [3] often need each human model whose inertial and geometric properties are known. The accurate motion analysis of each human subject requires the measurement or estimation of his/her parameters, and those techniques have been studied and developed [4], [5], [6], [7], [8], [9]. Non-invasive and simple technique becomes important for such a subject-specific analysis; on the other hand, a lot of properties of whole body segments also need to be obtained for the whole body analysis. Most techniques are difficult to satisfy both requirements.

In the field of robotics, the identification methods of a robot including a humanoid robot has been developed [10], [11], [12]. Based on the robotics technologies, the identification of human subject specific parameters has been studied [13], [14]. This paper presents the method to identify the geometric and inertial parameters of whole body segments by using motion capture system and force plates.

II. Inverse kinematics and dynamics analysis

Robotics computation theories are applied for human motion capturing in recent days [3]. Inverse kinematics computes the human joint trajectories from human motion capture data. Inverse dynamics can calculate the joint torques from joint trajectories and external forces from the ground and the contact objects. Fig.1 shows the flow of the analysis. They are introduced in this section.

A. Inverse kinematics

Let us model human skeletal system as a multi-body system. The system consists of N_L rigid bodies. It has a floating base-link whose generalized coordinates is represented by $\boldsymbol{q}_O \in SE(3)$. Each joint connecting bone is considered to be a mechanical one such as a rotational or spherical joint. Let N_J be the number of DOF of the system, and $\boldsymbol{q}_C \in \mathbb{R}^{N_J}$ be the joint angles. We now define $\boldsymbol{q} \triangleq [\boldsymbol{q}_O{}^T \ \boldsymbol{q}_C{}^T]^T$ as the whole generalized coordinates of the system.

Typical motion capture measures the position of the markers located on an object. Let N_M be the number of markers, $\boldsymbol{p}_i(\boldsymbol{q}) \in \mathbb{R}^3$ is the position of markers in the space, and $\widehat{\boldsymbol{p}}_i \in \mathbb{R}^3$ is the measured position of each marker. The inverse kinematics solves the nonlinear optimization problem to minimize the following cost function.

$$\min_{\boldsymbol{q}} \ \frac{1}{2}\sum_{i=1}^{N_M} \sigma_i ||\boldsymbol{p}_i(\boldsymbol{q}) - \widehat{\boldsymbol{p}}_i||^2 \tag{1}$$

where, $\sigma_i (> 0)$ is the weighting factor of the measurement error of each marker. There are several algorisms to solve the nonlinear optimization problem [15], and the efficient method for large-scale human musculoskeletal system has also been proposed [16].

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B. Inverse dynamics

The equations of motion of legged systems are given by Eq.(2).

$$\begin{bmatrix} \boldsymbol{H}_{OO} \, \boldsymbol{H}_{OC} \\ \boldsymbol{H}_{CO} \, \boldsymbol{H}_{CC} \end{bmatrix} \begin{bmatrix} \ddot{\boldsymbol{q}}_O \\ \ddot{\boldsymbol{q}}_C \end{bmatrix} + \begin{bmatrix} \boldsymbol{b}_O \\ \boldsymbol{b}_C \end{bmatrix} = \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{\tau} \end{bmatrix} + \sum_{k=1}^{N_c} \begin{bmatrix} \boldsymbol{J}_{Ok}{}^T \\ \boldsymbol{J}_{Ck}{}^T \end{bmatrix} \boldsymbol{F}_k^{ext} \tag{2}$$

where, $\boldsymbol{H}_{ij}(i,\ j = O,\ C)$ is the inertia matrix, $\boldsymbol{b}_i$ is the bias force vector including centrifugal, Coriolis and gravity forces, $\boldsymbol{\tau}$ is the vector of joint torques, N_c is the number of contact points with the ground or the devices attached on the human body, $\boldsymbol{F}_k^{ext} \in \mathbb{R}^6$ is the vector of external forces exerted to the system at contact k, $\boldsymbol{J}_k \triangleq [\boldsymbol{J}_{Ok} \ \ \boldsymbol{J}_{Ck}]$ is the basic Jacobian matrix associated to contact k.

In order to compute the joint torques from Eq.(2), we need to compute the other variables in Eq.(2). Inverse kinematics computes $\boldsymbol{q}_O$ and $\boldsymbol{q}_C$ from the position of markers. We can compute the numerical derivatives of them, and then obtain $\boldsymbol{H}_{ij}$ and $\boldsymbol{b}_i$. When the contact situation is known, $\boldsymbol{J}_k$ can be also computed. Contact forces $\boldsymbol{F}_k$ can be directly measured by force plates or force sensors. When evaluating the human motion using assistive devices, if the simulation model of the device is known or identified, $\boldsymbol{F}_k$ can be also estimated from the model [2]. In the case of multiple contact situation, $\boldsymbol{F}_k$ can be estimated by solving optimization problem [3].

III. Identification of human geometric parameters

Inverse kinematics problem Eq.(1) requires the geometric parameters of the skeletal model. This section presents an identification method of the geometric parameters [13].

Let N_ξ be the number of the geometric parameters, $\boldsymbol{\xi} \in \mathbb{R}^{N_\xi}$ be the constant geometric parameters. Marker position $\boldsymbol{p}_i(\boldsymbol{q}, \boldsymbol{\xi})$ is regarded as the function of not only $\boldsymbol{q}$ but also $\boldsymbol{\xi}$. Let us define N_T as the number of time samples, $t_1, t_2, \cdots, t_{N_T}$ as a time sequence of motion, $\widehat{\boldsymbol{p}}_i^{(t)}$ $(1 \leq t \leq N_T)$ as the measured positions of marker i at time instance t, and $\boldsymbol{q}^{(t)}$ $(1 \leq t \leq N_T)$ as the generalized coordinates at time instance t. Given $\widehat{\boldsymbol{p}}_i^{(t)}$ at all the time instances, let us solve the following problem.

$$\min_{\boldsymbol{q}^{(1)}, \cdots \boldsymbol{q}^{(N_T)}, \boldsymbol{\xi}} \quad \frac{1}{2} \sum_{t=1}^{N_T} \sum_{i=1}^{N_M} \sigma_i || \boldsymbol{p}_i(\boldsymbol{q}^{(t)}, \boldsymbol{\xi}) - \widehat{\boldsymbol{p}}_i^{(t)} ||^2 \tag{3}$$

Now, let us represent $\boldsymbol{\xi}$ as the generalized coordinates of virtual mechanical joints. For example, the length between two joints can be represented as a coordinate of one translational joint. With the generalized coordinates of virtual joints, the inverse problem to compute $\boldsymbol{\xi}$ can be also regarded as robotic inverse kinematics. Therefore, Eq.(3) means that the large-scale inverse kinematics problem to compute simultaneously the generalized coordinates $\boldsymbol{q}^{(t)}$ at all the time instances and the virtual coordinates $\boldsymbol{\xi}$ that is time-invariant through all the instances. Hence, the solution can be obtained by applying straightforwardly the recent large-scale inverse kinematics technique [16].

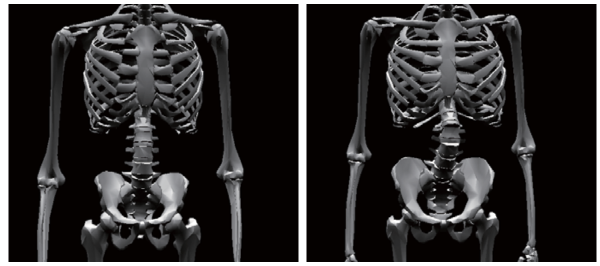

Fig. 2. Comparison of the inverse kinematic results between the two models: the identified model (Left), the template model scaled by the body height of a subject (Right).

The similar formula is found in the methodology used in the calibration of serial robot chains, where both the kinematics parameters and constant joint offsets [10]. The critical difference between the calibration of robots and humans is whether or not the joint angles can be measured directly, for example, by encoders. Therefore, the human joint angle trajectories and the geometric parameters generally have to be identified simultaneously.

The method was applied to obtain a subject-specific parameters of the human musculoskeletal model shown in [3]. The exercise motion of the whole body was recorded for the identification. In the only identification process, the low-dimensional model was used; some bones were grouped in order to avoid the identifiability problem. After the identification, the walking motions were also recorded by the motion capture system. For the validation, the two models were used for the inverse kinematics; (A). the identified model, and (B). the template model simply scaled by the body height of a subject. Fig.2 shows the comparison of the inverse kinematic results between the two models at a certain time instance during the walking motion. In the figure, the muscles are not drawn for illustrative purposes. In the case of the scaled template model, the spine was bent awkwardly because the model is not fitting to a subject. Therefore, the muscle lengths around the spine contained the significant errors. Such kind of a situation often happens, when the ratio of the length of body segments of a subject is different to some extent from that of the template model. The proposed method can obtain a subject-specific human model, which can enhance the accuracy of musculoskeletal analysis.

IV. Identification of human inertial parameters

When computing the joint torque from inverse dynamics model Eq.(2), not only the geometric parameters but also the inertial parameters assume to be known. This section shows the identification method of the inertial parameters.

The equations of motion of multi-body systems can be written in a linear form with respect to the inertial parameters [17], [11], and Eq.(2) can be transformed to as followings:

$$\begin{bmatrix} \boldsymbol{Y}_O \\ \boldsymbol{Y}_C \end{bmatrix} \boldsymbol{\phi} = \begin{bmatrix} \boldsymbol{F}_O \\ \boldsymbol{F}_C \end{bmatrix} \triangleq \begin{bmatrix} \boldsymbol{0} \\ \boldsymbol{\tau} \end{bmatrix} + \sum_{k=1}^{N_c} \begin{bmatrix} \boldsymbol{J}_{Ok}{}^T \\ \boldsymbol{J}_{Ck}{}^T \end{bmatrix} \boldsymbol{F}_k^{ext} \tag{4}$$

where, $\boldsymbol{\phi} \in \mathbb{R}^{10 N_L}$ is the vector of the inertial parameters of whole body segments. Each body segment has 10 parameters:

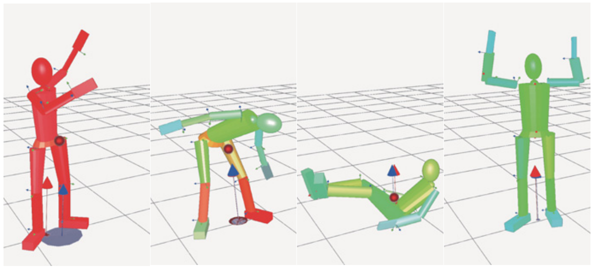

Fig. 3. The visualization interface to display the results of real-time identification. The color of each link shows the degree of progress of identification: red parts are not yet estimated, and green parts are successfully identified. Red arrow is the force plate measurement of contact force, blue arrow is the reconstructed contact force from identified dynamics. The red ball is the total center of mass computed from identified parameters.

mass, center of mass, and inertia tensors [11]. Coefficient matrices $\boldsymbol{Y}_{BO}$ and $\boldsymbol{Y}_{BC}$ are called regressor matrices.

Most common identification methods in the robotics field utilize liner form Eq.(4), and need to know all the variables except $\boldsymbol{\phi}$. However, it is difficult to measure human joint torques directly. Inverse dynamics Eq.(2) also cannot be computed because $\boldsymbol{\phi}$ is unknown. Now, let us formulate the following least squares problem:

$$\min_{\boldsymbol{\phi}} \ \omega_1 \sum_{t}^{N_T} ||\boldsymbol{Y}_O{}^{(t)}\boldsymbol{\phi} - \boldsymbol{F}_O{}^{(t)}||^2 + \omega_2 ||\boldsymbol{\phi} - \widehat{\boldsymbol{\phi}}||^2 \qquad (5)$$

The first term of Eq.(5) evaluates the error about only the upper part of Eq.(4): the equations of the base-link, which does not contain $\boldsymbol{\tau}$. It has been proven that the number of the structural identifiable parameters from the base-link dynamics is the same when using the whole equations [12]. Therefore, in principle, we can perform the identification even without torque measurement. The second term of evaluates the error from a-priori knowledge $\widehat{\boldsymbol{\phi}}$ about the inertial parameters which can be obtained from literatures and databases. Some set of inertial parameters have no effect on the equation of motions. It is known that they cannot be structurally identified [11]. The performance of identification also depends on the motion trajectory used for the identification [11]. A-priori parameters $\widehat{\boldsymbol{\phi}}$ is used for those unidentifiable or less identifiable parameters.

Since the problem Eq.(5) can be solved iteratively, the real-time identification can be realized during motion capturing. One useful application of the real-time identification is the visualization of the identification result [14]. The outline of the visualization is shown in Fig.3; the color of each link changed gradually with the progress of the identification procedure. The human subject can immediately check the body segments yet to be identified, and intuitively know which body part should be moved. Since the performance of identification depends on the motion trajectory, the visualization can improve the quality of identification results. Fig.3 also shows that the estimated contact forces from the identified results (blue arrow) were gradually converged to the measured forces (red arrow). Hence, the method is expected to enhance the accuracy of inverse dynamics analysis.

V. Conclusion

The paper presents the method to identify the human geometric and inertial parameters for subject-specific modeling. When evaluating assistive devices, the estimation of human joint trajectories and torques has an important role. The inverse kinematics and dynamics analysis by motion capturing require the geometric and inertial parameters of the human model. Our approach can identify the whole-body parameters non-invasively by using standard motion capture system and force plates, which is expected to lead the accurate evaluation of the assistive effects on human bodies.

References

[1] K. Miura, E. Yoshida, Y. Kobayashi, Y. Endo, F. Kanehioro, K. Homma, I. Kajitani, Y. Matsumoto, and T. Tanaka, "Humanoid robot as an evaluator of assistive devices," in *Proc. of the IEEE Int. Conf. on Robotics and Automation*, 2013, pp. 671–677.

[2] K. Ayusawa, S. Nakaoka, E. Yoshida, Y. Imamura, and T. Tanaka, "Evaluation of assistive devices using humanoid robot with mechanical parameters identification," in *Proc. of the IEEE-RAS Int. Conf. on Humanoid Robots*, 2014, pp. 205–211.

[3] Y. Nakamura, K. Yamane, K. Fujita, and I. Suzuki, "Somatosensory computation for man-machine interface from motion-capture data and musculoskeletal human model," *IEEE Trans. on Robotics*, vol. 21, no. 1, pp. 58–66, 2005.

[4] S.S. Gamage and J. Lasenby, "New least squares solutions for estimating the average centre of rotation and the axis of rotation," *J. of Biomechanics*, vol. 35, no. 1, pp. 87–93, 2002.

[5] A.G. Kirk, J.F. O'Brien, and D.A. Forsyth, "Skeletal parameter estimation from optical motion capture data," in *Proc. of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2005, vol. 2, pp. 782–788.

[6] R.K. Jensen, "Estimation of the biomechanical properties of three body types using a photogrammetric method," *J. of Biomechanics*, vol. 11, pp. 349–358, 1978.

[7] D.J. Pearsall and J.G. Reid, "Inertial properties of the human trunk of males determined from magnetic resonance imaging," *Annals of Biomedical Engineering*, vol. 22, pp. 692–706, 1994.

[8] C.K. Cheng, "Segment inertial properties of chinese adults determined from magnetic resonance imaging," *Clinical biomechanics*, vol. 15, pp. 559–566, 2000.

[9] A.L. Betker, T. Szturm, and Z. Moussavi, "Center of mass approximation during walking as a function of trunk and swing leg acceleration," in *Proc. of the 28th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society*, 2006, pp. 3435–3438.

[10] John M. Hollerbach and Charles W. Wampler, "The calibration index and taxonomy for robot kinematic calibration methods," *Int. J. of Robotics Research*, vol. 15, no. 6, pp. 573–591, 1996.

[11] W. Khalil and E. Dombre, *Modeling, identification and control of robots*, Hermès Penton, London-U.K, 2002.

[12] K. Ayusawa, G. Venture, and Y. Nakamura, "Identifiability and identification of inertial parameters using the underactuated base-link dynamics for legged multibody systems," *Int. J. of Robotics Research*, vol. 33, no. 3, pp. 446–468, 2014.

[13] K. Ayusawa, Y. Ikegami, and Y. Nakamura, "Simultaneous global inverse kinematics and geometric parameter identification of human skeletal model from motion capture data," *Mechanism and Machine Theory*, vol. 74, pp. 274–284, 2014.

[14] G. Venture, K. Ayusawa, and Y. Nakamura, "Optimal estimation of human body segments dynamics using realtime visual feedback," in *Proc. of the IEEE/Int. Conf. on Intelligent Robot System*, 2009, pp. 1627–1632.

[15] R. Fletcher, *Practical Methods of Optimization; (2Nd Ed.)*, Wiley-Interscience, New York, NY, USA, 1987.

[16] K. Ayusawa and Y. Nakamura, "Fast inverse kinematics algorithm for large DOF system with decomposed gradient computation based on recursive formulation of equilibrium," in *Proc. of the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 2012, pp. 3447–3452.

[17] C.-G. Atkeson, C.-H. An, and J.-M. Hollerbach, "Estimation of inertial parameters of manipulator loads and links," *Int. J. of Robotic Research*, vol. 5, no. 3, pp. 101–119, 1986.