31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

Monitoring The Segment Parameters During Long Term Physical Training From Motion Capture Data

Gentiane Venture[1], Ko Ayusawa[2], Dana Kulic[3], Yoshihiko Nakamura[2]

***Abstract*— The segment parameters (SP) consisting of inertia and position of the center of mass of each segment, of the human body are crucial data when one wants investigate motion dynamics. The segment parameters vary with time according to immobilization, physical training, rehabilitation, muscular diseases. This knowledge provides valuable information to support medical diagnosis and to quantify the effect of medical treatment, rehabilitation or training. However they are usually difficult to measure in-vivo for these kinds of applications and thus are not specifically used. In this paper we propose to apply a previously developed identification method in order to monitor the evolutions of those parameters over 5 months, during which the candidate followed a 16-week marathon training before running the 2009 Tokyo Marathon. The motion data is recorded on a weekly basis and the parameters are computed after each session. The obtained results are presented and the changes in body SP are discussed in the light of typical results occurring to the body fitness.**

I. Introduction

The segment parameters (SP) of the human body i.e., the mass, the inertia and the center of mass positions of each segment, are of crucial importance to study human motion dynamics in biomechanics studies, in gait studies and for medical applications as orthopedics, neurology, and musculoskeletal disorders studies. With accurate SP, it is possible to refine diagnosis and adjust health-care to the patient. The computation of the segment parameters (SP) is a key-step in gait analysis and to monitor the variations of muscle mass due to disease, hospitalization, rehabilitation or training. The most utilized method to estimate the SP is the use of CT-scan or MRI and 3D modeling. However this method cannot be used intensively due to radiation exposure. Given the difficulties in using an appropriate (safe, repeatable, efficient) method, properly identified subject-specific parameters are rarely used. Although recently portable systems allow the computation of the whole-body COM [1], [2] individual SP are not estimated in-vivo. In addition, when using literature data, as there is no uniformity neither in the landmarks nor in the models of the human-body used [3]; and a profusion of references, an adequate choice fitting with the population under study is difficult. Moreover, to properly interpolate the available data, massive geometric measurements are often necessary. Nevertheless, it is shown in [4] that errors in the value of the SP affect significantly the analysis results. Consequently, there was a pressing need to develop reliable and robust methods to estimate in-vivo the SP of the human body. In our previous works, we have developed an identification method of base-parameters of the human body [5] based on motion capture data and contact force measurement, systems often used for gait analysis. In this paper we propose to investigate the possibility to use this method for the monitoring of the SP during a 5 months physical training for one marathon runner. The subject motion data and force data [6] are recorded on a weekly basis. The motion performed is from a daily gymnastic TV programm that we have shown to be sufficient to excite the dynamics to identify [7]. The paper is organized as follows: in section II we describe the main features of the identification method. In section III we detail the experimental environment and the training schedule. Finally in section IV we present and discuss the obtained results.

This research is supported by the Special Coordination Funds for Promoting Science and Technology: "IRT Foundation to Support Man and Aging Society".

[1] Department of Mechanical System Engineering, Tokyo University of Agriculture and Technology
[2] Department of Mechano-Informatics, The University of Tokyo, Japan
[3] Department of Electrical and Computer Engineering, University of Waterloo
Corresponding author: G. Venture venture@cc.tuat.ac.jp

II. Identification from base-link dynamics and contact force information

A. Modeling the human body dynamics

To obtain accurate identification 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 [5], the modeling depends on the purpose of identification and the real constraints such as the measurement facility. We consider a model of the human body consisting of 34 DOF and 15 rigid links as described in Table I and Fig. 1. It represents the most important DOF that are used in daily activities such as locomotion. DOF can be added and removed as needed, keeping in mind that a compromise is necessary between the number of DOF and the identifiability (smallness, excitation) of the SP. The geometric parameters of the human body need to be measured. Usually they would be measured manually, here we use an automatic method making use of the passive optical reflective marker positions as will be defined in section III. Examples of resulting models are given in Fig. 1. They 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.

TABLE I

CHOSEN DOF IN THE MODEL OF THE HUMAN BODY

name of joint	type of joint	number of DOF
neck	spherical	3
waist	spherical	3
right shoulder	spherical	3
right elbow	revolute	1
right wrist	spherical	3
left shoulder	spherical	3
left elbow	revolute	1
left wrist	spherical	3
right hip	spherical	3
right knee	revolute	1
right ankle	spherical	3
left hip	spherical	3
left knee	revolute	1
left ankle	spherical	3

B. Identification model of legged systems

This kinematic model leads to a 128×1 vector of base parameters $\boldsymbol{\phi}_B$ to be identified and given by Eq. 1.

$$\boldsymbol{\phi}_B = \left[\boldsymbol{\phi}_{B0}^T \ \boldsymbol{\phi}_{B1}^T \ ... \ \boldsymbol{\phi}_{B14}^T\right]^T \tag{1}$$

such that:

$$\boldsymbol{\phi}_{Bi} = \begin{cases} [M_i \, MS_{i,x} \, MS_{i,y} \, MS_{i,z} \, J_{i,xx} \\ \quad J_{i,yy} \quad J_{i,zz} \quad J_{i,yz} \quad J_{i,zx} \, J_{i,xy}]^T & (i=0) \\ \\ [MS_{i,x} \, MS_{i,y} \, J_{i,xx} - J_{i,yy} \, J_{i,zz} \\ \qquad J_{i,yz} \qquad J_{i,zx} \, J_{i,xy}]^T & revolute \\ \\ [MS_{i,x} \, MS_{i,y} MS_{i,z} \, J_{i,xx} \, J_{i,yy} \\ \quad J_{i,zz} \qquad J_{i,yz} \qquad J_{i,zx} \, J_{i,xy}]^T & spherical \end{cases}$$

where:

- M_i is the base parameter of link i representing the sum of the masses of links that are lower in the chain: $M_{i-1} = m_{i-1} + M_i$,
- MS_i is the base parameter of link i representing the sum of the first moment of inertia, for i from 15 to 1: $\boldsymbol{MS}_{i-1} = \boldsymbol{ms}_{i-1} + M_i{}^{i-1}\boldsymbol{p}_i + {}^{i-1}\boldsymbol{r}_i$,

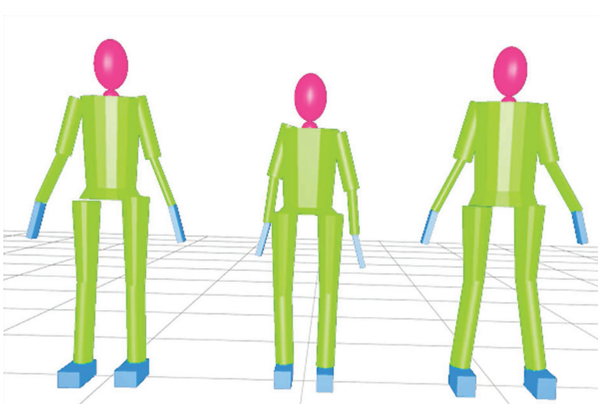

Fig. 1. Model of the kinematic structure of the human body with 34 DOF for 3 different morphologies

- J_i is the base parameter of link i representing the inertia, for i from 15 to 1:

$$\begin{aligned} \boldsymbol{J}_{i-1} &= \boldsymbol{I}_{i-1} + M_i[{}^{i-1}\boldsymbol{p}_i\times]^T[{}^{i-1}\boldsymbol{p}_i\times] \\ &+ [{}^{i-1}\boldsymbol{p}_i\times]^T[{}^{i-1}\boldsymbol{r}_i\times] + [{}^{i-1}\boldsymbol{r}_i\times]^T[{}^{i-1}\boldsymbol{p}_i\times] \\ &+ J_{i,yy}{}^{i-1}\boldsymbol{R}_i\boldsymbol{U}^{i-1}\boldsymbol{R}_i^T \end{aligned}$$

- $[\boldsymbol{v}\times]$ according to [8] is given by:

$$[\boldsymbol{v}\times] = \begin{bmatrix} 0 & -v_z & v_y \\ v_z & 0 & -v_x \\ -v_y & v_x & 0 \end{bmatrix} \tag{2}$$

- ${}^{i-1}\boldsymbol{R}_i$ is the rotation matrix from the frame attached to link $i-1$ to the frame attached to link i,
- ${}^{i-1}\boldsymbol{p}_i$ is the translational vector from the frame attached to link $i-1$ to the frame attached to link i,
- ${}^{i-1}\boldsymbol{r}_i$ and $\boldsymbol{U}$ defined as follow:

$${}^{i-1}\boldsymbol{r}_i = {}^{i-1}\boldsymbol{R}_i \begin{bmatrix} 0 \\ 0 \\ MS_{i-1,z} \end{bmatrix}, \boldsymbol{U} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

It corresponds to a regressor with 128 columns; it is decomposed in 15 sub-regressors (one for each link) as shown in Eq. 3, where each sub-regressor has as many columns as its attached link has base parameters.

$$\left[\ \boldsymbol{Y}_{B_{link0}} \ \boldsymbol{Y}_{B_{link1}} \ \ldots \ \boldsymbol{Y}_{B_{link14}} \ \right] \tag{3}$$

C. Motion selection for identification

Usually exciting the whole dynamics of a complex system with only one motion is impossible. Using the linearity in the parameters to estimate the identification model, it is common to use a vertical concatenation of M different prescribed motions that each excites specific dynamics to create the regressor [9], [10], as shown in Eq. 4.

$$\begin{bmatrix} \boldsymbol{Y}_{B_{motion1}} \\ \boldsymbol{Y}_{B_{motion2}} \\ \vdots \\ \boldsymbol{Y}_{B_{motionM}} \end{bmatrix} \boldsymbol{\phi}_B = \begin{bmatrix} \boldsymbol{E}_{motion1} \\ \boldsymbol{E}_{motion2} \\ \vdots \\ \boldsymbol{E}_{motionM} \end{bmatrix} \tag{4}$$

The actual excitation properties of the motion are verified a-posteriori by looking at the condition number of each individual regressor and at the resulting regressor [10]. However with complex systems it is difficult to interpret directly the obtained values of the condition number of the regressor and to understand the actual excitation properties in detail as two regressors, obtained with two different motions, can have the same condition number as it will be detailed in section IV. In that case, to limit the computation time it is necessary to closely look at the executed motions to define their excitation properties and chose the appropriate motions to concatenate. Thus systematic identification is not possible and post-processing is a manual, time-consuming task.

In [11] we have proposed an approach to select systematically the persistent exciting trajectories from a set of recorded data. It consists of looking at the condition number of the $N_s + 1$ sub-regressors obtained for one link - or one group of links - and to systematically extract excitation features for each motion and to concatenate motions that excite the dynamics optimally (i.e. fewer data, better excitation). To find the proper set of motions we proceed in two steps to finally obtain an optimal data-set with a minimum number of motions that maximize the excitation of the dynamics to estimate.

III. Experimental setup

The motions are recorded by an optical motion capture system consisting in 10 cameras (Motion Analysis). We use 35 passive reflective markers attached to the body of the subject. These markers are located at the defined anatomical points to insure accuracy of inverse kinematics computations as can be shown from Fig. 2, and to automatically compute the geometric parameters of each link by measuring the relative position of the markers. The contact forces are measured by 2 force-plates (Kistler). The inverse kinematics, to obtain the joint angles and their derivatives, is computed by an in-house software [12] using the human model previously defined in section II.1.

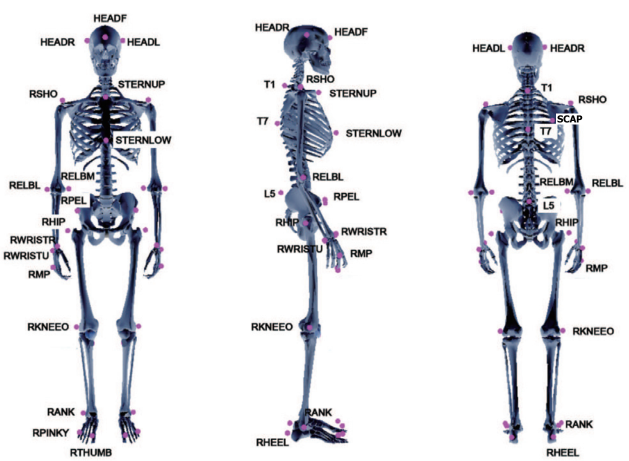

Fig. 2. Marker-set used for the motion capture

The motions recorded are predefined and performed in 3 sequences. They are motions from a daily gymnastic TV program [13]. We have proven that these motions provide sufficient excitation to identify the SP [11]. The motion segmentation is manual. The selection of motions and the identification are performed according to section II.2.

The data used was collected over five months during the course of a marathon training program. The subject, a 33 year old female, undertook the Stanton marathon training program in preparation for the 2009 Tokyo Marathon. The training program is a 16 week program, specifying a 5-days a week running schedule which gradually increases the running distance covered from 20km per week in the first week, to a maximum of 80km per week in the peak 13th week, before tapering in the final 3 weeks before the race. Prior to the start of the marathon training, the subject was running on average 25km per week. During the course of the training program, the subject was recorded on a weekly basis in a motion capture studio equipped with force plates. On several weeks over the course of the training program, recording sessions were omitted due to availability constraints and the candidate's health condition. At each session similar sequences of motions are recorded. To facilitate their execution a video of the motion is shown.

IV. Experimental results

After each session of measurement, the data are processed to identify the inertial parameters. A summary of the obtained results is given in Fig. 3. It shows the evolution of the parameters for the upper torso, the lower torso, both thighs and both shanks. Parameters for the arms, the head and the foot are not significantly varying which is consistent with the training undertaken. The bottom line of the figure summarizes the marathon training and the health condition of the candidate. The vertical lines highlight the beginning of the training (week 1), the recovery of training after illness (at the end of week 7) and the peak of the training (at the end of week 13). The parameters are given in standard units.

According to sports specialists and to existing study on elite sport women [14] it is expected that the body fitness will change dramatically during the training. First an increase of total mass corresponding to the muscle development, then a period of mass loss, corresponding to the loss of fat before stabilization. The fat-free mass increase accompanies a change in the inertial parameters and slightly in the vertical location of the center of mass of each link. Long runs also provoke the secretion of cortisol which inhibits protein synthesis and thus leads to muscle mass loss.

As can be seen from the results, the total mass M of the subject is varying between 58 Kg and 61 Kg over the training period. As expected it starts to rise when the training starts and then decreases, however it drops after the illness, to recover its value at week 10 and then slowly decreases when the training intensity augments, as was expected. Most of the parameters follow a similar pattern: important changes at the beginning of the training, then slow changes; an abrupt change after the illness period; 2 weeks to recover their normal value, to abruptly change again after the peak of the training in week 13. Similar changes can be observed in the inertial parameters of both thighs and shanks, that can be attributed to the symmetry of the training. The changes in the thigh and the shank are relatively more important than the changes in the other links. That can be explained by the fact that this is the place where the most important changes occur in term of tissue changes: adipose tissues/muscular tissues. During the long run they are also the most affected tissues corresponding to a greater muscle mass loss.

V. Conclusion

This paper presents a method to estimate the segment parameters of the human body and its application to the monitoring of segment parameters during a 16 weeks marathon training for a female candidate. The proposed method is based on motion and contact force measurements. To optimize the quality of the identification results the motions performed by the subject at each measurement session are predefined. They are taken from a daily gymnastic TV program. To help with performing the same motions a video of the motions is shown simultaneously to their execution. The post processing of the data includes systematic selection of the best motion for identification based on consideration of the condition number of the sub-regressor matrices. The obtained results have shown that it is possible to monitor the changes in the inertial parameters over a long-time period. The changes observed are consistent with the events occurring during the training period and there is also a good consistency with right and left leg parameters. The most important relative changes occur in the legs. This can be explained by the type of training. The parameters of the upper limbs are sensibly not changing. The obtained results are of importance as they provide a safe and flexible environment to monitor the evolution of the SP during sports training. It can also be utilized for the monitoring of SP during rehabilitation, drug tests that affect the body constitution and to a larger extent to healthcare and fitness.

References

[1] 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 IEEE EMBS Annual Int. Conf., New York City, USA*, 2006, pp. 3435–3438.

[2] J. Han, A.L. Betker, T. Szturm, and Z. Moussavi, "Estimation of the center of body mass during forward stepping using body aceleration," in *Proc. of the 28th IEEE EMBS Annual Int. Conf., New York City, USA*, 2006, pp. 4564–4567.

[3] P. de Leva, "Adjustments to zatsiorsky-seluyanov's segment inertia parameters," *J.of Biomechanics*, vol. 29, no. 9, pp. 1223–1230, 1996.

[4] D.J. Pearsall and P.A. Costigan, "The effect of segment parameter error on gait analysis results," *Gait and Posture*, vol. 9, pp. 173–183, 1999.

[5] G. Venture, K. Ayusawa, and Y. Nakamura, "Motion capture based identification of human inertial parameters," in *Proc. IEEE/EMBS Int. Conf. on Eng. in Medicine and Biology*, 2008, pp. 4575–4578.

[6] G. Venture, K. Ayusawa, and Y. Nakamura, "Dynamics identification of humanoid systems," in *Proc. CISM-IFToMM Symp. on Robot Design, Dynamics, and Control (ROMANSY)*, 2008, pp. 301–308.

[7] G. Venture, K. Ayusawa, and Y. Nakamura, "Identification of human mass properties from motion," in *IFAC Symposium on System Identification*, 2009, p. under review.

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

[9] H. Mayeda, K. Osuka, and A. Kangawa, "A new identification method for serial manipulator arms," in *Proc. IFAC 9th World Congress*, 1984, pp. 2429–2434.

[10] G. Venture, P.J. Ripert, W. Khalil, M. Gautier, and P. Bodson, "Modeling and identification of passenger car dynamics using robotics formalism," *IEEE Trans. on Intelligent Transportation Systems*, vol. 7, no. 3, pp. 349–359, 2006.

[11] G. Venture, K. Ayusawa, and Y. Nakamura, "A numerical method for choosing motions with optimal excitation properties for identification of biped dynamics - an application to human," in *Proc. IEEE Int. Conf. on Robotics and Automation (to be published)*, 2009, pp. 1226–1231.

[12] Y. Nakamura, K. Yamane, I. Suzuki, and Y. Fujita, "Dynamic computation of musculo-skeletal human model based on efficient algorithm for closed kinematic chains," in *Proc. of the 2nd Int. Symp. on Adaptive Motion of Animals and Machines*, March 2003.

[13] Nihon Hoso Kyokai Japan Broadcasting Corporation, "NHK terebi taisou," DVD.

[14] C. Granados, M. Izquierdo, J. Ibanez, M. Ruesta, and E. Gorostiaga, "Effects of an entire season on physical fitness in elite female handball players," *Medicine and Science in Sports and Exercise*, pp. 351–361, 2007.

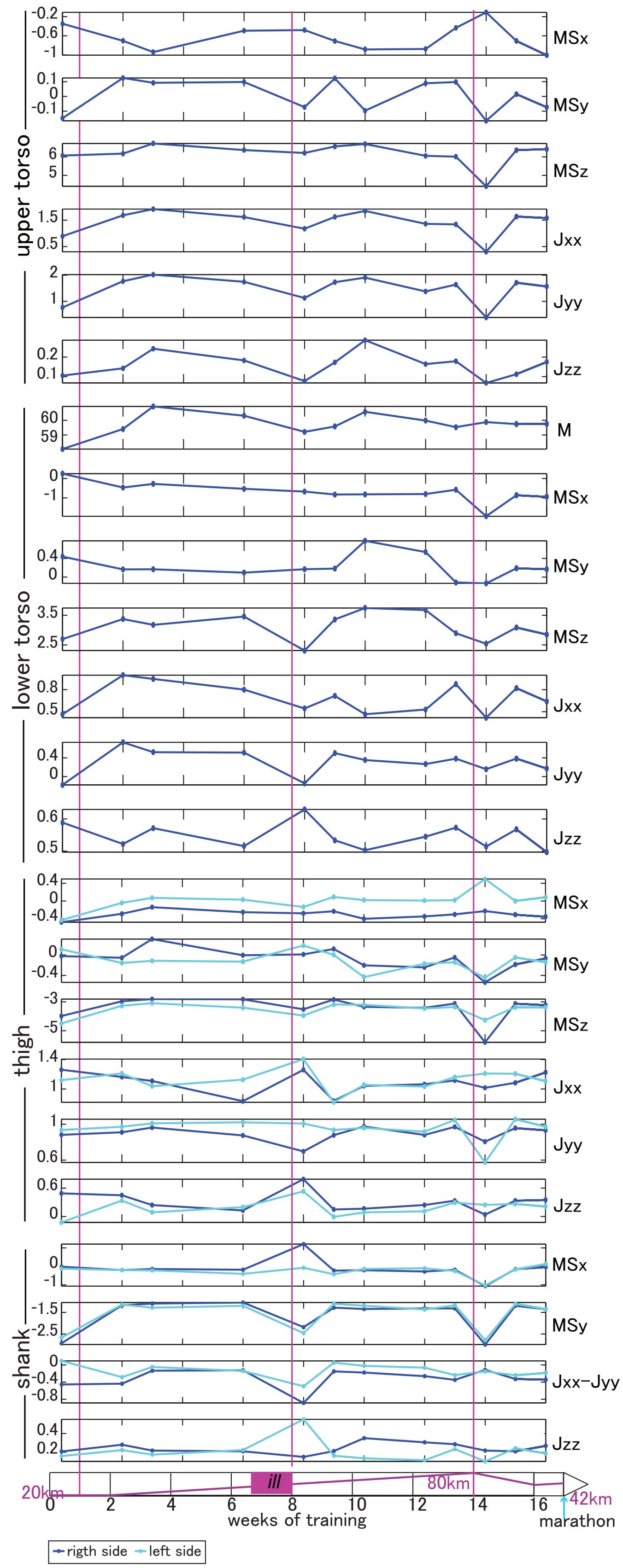

Fig. 3. Identification results for the upper torso, the lower torso, the thighs and the shanks during the 16 weeks of training