筋骨格力学モデルとモーションキャプチャを用いた人間の関節の受動的スティフネスの推定とその医療応用

○ Gentiane Venture： 東京大学，〒113-8656 東京都文京区本郷 7-3-1
gentiane@ynl.t.u-tokyo.ac.jp
中村仁彦 ： 東京大学，〒113-8656 東京都文京区本郷 7-3-1
nakamura@ynl.t.u-tokyo.ac.jp
山根克 ： 東京大学，〒113-8656 東京都文京区本郷 7-3-1
yamane@ynl.t.u-tokyo.ac.jp

Passive Stiffness Estimation of Human Joints and its Medical Applications Based on Musculoskeletal Dynamics Model and Motion-Capturing

○ Gentiane VENTURE: University of Tokyo Yoshihiko NAKAMURA: University of Tokyo
Katsu YAMANE: University of Tokyo

ABSTRACT: Human joints dynamics is very important in the fields of humanoid robotics, medical robotics as well as medical research. For example medical diagnosis of muscle or neuro-motor diseases are based on a visual qualitative estimation of joint passive stiffness and there is a pressing need in human body subject specific dynamics characterization. This paper presents a global solution to estimate in-vivo the passive dynamics of the human limbs joint. It is based on the use of the musculo-skeletal description of the human body and its kinematics and dynamics computations. The linear passive joint dynamics: stiffness, viscosity and friction, is then estimated with linear least squares method. Acquisitions of movements during medical diagnosis check-up are achieved in a motion capture studio and are guaranteed to be painless. Experimental results are given.

keywords: human dynamics, inverse dynamics, musculoskeletal human model, motion capture

1. Introduction

The human body is a very complex and fascinating system. It is able of sensing, analyzing, deciding and moving thanks to the nervous system, the brain and the musculo-skeletal system. It is fast, accurate, well-coordinate, compact and powerful, capable of amazing achievements which most impressive examples can be violin prodigy, surgeon, funambulist or fencing master. Nevertheless when injured, ageing or suffering from neuro-motor disease such as Parkinson or cerebral palsy, movement disorders and cognitive disorders appear. As such disorders threaten the quality of life of both patient and relatives they are not only an important medical issue, but also a social issue, more particularly in the countries were population is ageing. In that context the study of the human body leading to a sharpened knowledge of the movements generation and control is expressly required.

Medical diagnosis check-up of neuro-muscular diseases gives only visual appreciation of rigidity of the body joints and for people suffering from slow evolutional neuro-motor diseases such as Parkinson disease and it is difficult to have a clear appreciation of occurring changes at each check-up. An important reason to focus research on the human joint dynamics is to give medical researchers on muscles and neuro-motor diseases a tool to enhanced the accuracy of their diagnosis by giving a quantification of joint rigidity of people suffering from those diseases and helping them in designing and performing more relevant tests.

Many researches are focusing on the modelling of the musculo-skeletal system in order to understand and simulate the human movements [1], [2], [3], [4]. They are based on anatomical musculo-skeletal geometric descriptions of the human body, and thanks to enhancements of computation power accurate models can now be used. Those models are commonly used to compute kinematics and dynamics such as joint angles and joint torques from the recorded position of optical markers. Markers are paste on the body and their position is captured by *motion capture* video cameras. Fields of application are boundless: sport science, rehabilitation, virtual reality, computer aided animation, video games.

As a matter of fact this paper proposes an original method to estimate ***in-vivo*** the human joint dynamics for passive movements. It is painless and required only a motion capture studio. This method that as been successfully applied to the elbow joint [5] is now developed to multi-joint applications. It is based on the use of a musculo-skeletal dynamics computation and a linear modelling of the human joints dynamics: stiffness, viscosity and friction. The sampled linear over-determinate system obtained along a movement from the medical diagnosis is solve with least squares method. Standard deviation and condition number are also computed to help interpreting the obtained results. The experimental setup is described and experimental results are finally given and discussed.

2. Modelling the human body

Powerful robotics formalisms, such as Modified Denavit Hartenberg formalism [6], allow to describe systems as multi-body systems linked by joints. Such description has been applied to manipulator robots, mobile robots [7], [8] as well as biologically inspired robots [9] with complex structures: tree or parallel. Though it has to be taken into account that due to the high number of degrees of freedom of the human body and to changes that can occur in the kinematics chain, such formalisms have been enhanced and developed for the specific human body based on musculo-skeletal approach [1], [3]. Those modelling methods allow to compute easily the inverse kinematics as well as the inverse dynamics for the whole human body. The model used has 366 muscles driving a skeleton with 155 degrees of freedom (DOF). The inverse dynamics can be written:

$$\mathbf{\Gamma} + \boldsymbol{Q} = \mathbf{\Gamma}^e + \mathbf{\Gamma}^v + \mathbf{\Gamma}^f + \boldsymbol{H}\left(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}, \boldsymbol{D}_P\right) \qquad (1)$$

where:

- $\boldsymbol{q}$ the vector of joint angle q_j, $\dot{\boldsymbol{q}}$ and $\ddot{\boldsymbol{q}}$ its first and second time derivatives,
- j denotes the concerned joint in the chain and the following body attached to it,
- $\boldsymbol{D}_P$ the vector of inertial parameters of the system: mass, inertia, first moment of inertia,
- $\mathbf{\Gamma}$ is the vector of joint forces or torques
- $\boldsymbol{Q}$ is the vector of generalized efforts representing the projection of the external forces and torques on the joint axes, it is calculated with:

$$\boldsymbol{Q} = -\sum \boldsymbol{G}_j(\boldsymbol{q})^T \boldsymbol{F}_{ej} \qquad (2)$$

- $\boldsymbol{G}_j(\boldsymbol{q})$ is the Jacobian matrix of the frame of body j
- $\boldsymbol{F}_{ej}$ is the vector of external forces and moments applied by body j on the environment,
- $\boldsymbol{H}$ is the vector of inertial, Coriolis, centrifugal and gravity forces,
- $\mathbf{\Gamma}^e$ is the joint elastic force. The j^{th} element of $\mathbf{\Gamma}_e$ is written as:
  - if j has elasticity:

$$\Gamma_j^e = k_j(q_j - q_j^r) \qquad (3)$$

    with k_j the stiffness of joint j, q_j^r the natural rest joint angle induced by gravity,
  - if j is not an elastic joint $\Gamma_j^e = 0$
- $\mathbf{\Gamma}^v$ is the joint viscosity force with h_j the viscous coefficient:

$$\Gamma_j^v = h_j \dot{q}_j \qquad (4)$$

- $\mathbf{\Gamma}^f$ is the friction force. It is modelled by Coulomb coefficient f_j:

$$\Gamma_j^f = f_j sign(\dot{q}_j) \qquad (5)$$

The inertial parameters $\boldsymbol{D}_P$ are known. They can be estimated from previous experiments requesting force sensors or torque-meter, or scaled from literature's available parameters [10]. Moreover the estimation is achieve for passive movements of the joints , though $j = n_j$ and the vector of external forces $\boldsymbol{F}_{ej}$ is zero in (2), consequently $\boldsymbol{Q} = \mathbf{0}$. (1) then becomes for each joint j:

$$\mathbf{\Gamma}_j - \boldsymbol{H}_j\left(\boldsymbol{q}_j, \dot{\boldsymbol{q}}_j, \ddot{\boldsymbol{q}}_j, \boldsymbol{D}_{Pj}\right) = k_j(q_j - q_j^r) + h_j\dot{q}_j + f_j sign(\dot{q}_j) \qquad (6)$$

where the left side is known: inertial effects of the limb, and the right one contents the joint dynamic parameters to estimate: k_j, h_j and f_j.
The chosen model of the joint is linear in the parameters to estimate and can be written as:

$$\boldsymbol{T} = \boldsymbol{D}\left(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}\right)\boldsymbol{X} \qquad (7)$$

- $\boldsymbol{X}$ the $(3n_j \times 1)$ vector of parameters to be estimated, $\boldsymbol{X} = [\boldsymbol{X}_1 \ldots \boldsymbol{X}_j \ldots \boldsymbol{X}_{n_j}]$ where $\boldsymbol{X_j} = [k_j\ h_j\ f_j]^T$
- $\boldsymbol{D}$ is the $(n_j \times 3n_j)$ vector function of joint angle q and its first and second derivatives,
- $\boldsymbol{T}$ is computed by $\mathbf{\Gamma} - \boldsymbol{H}\left(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}, \boldsymbol{D}_P\right)$

To solve this system linear least squares optimization techniques is used [6], [11].
The dynamic model (6) is sampled along an exciting movement. All the n_e samples give a linear system of equations:

$$\boldsymbol{Y} = \boldsymbol{W}\left(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}\right)\boldsymbol{X} + \boldsymbol{\rho} \qquad (8)$$

where:

- $\boldsymbol{Y}$ is the $(n_e n_j \times 1)$ vector of joint torques, obtained by sampling $\boldsymbol{T}$
- $\boldsymbol{W}$ is the $(n_e n_j \times 3n_j)$ observation matrix (or regressor matrix), obtained by sampling $\boldsymbol{D}$
- $\boldsymbol{\rho}$ the $(n_e n_j \times 1)$ vector of modelling errors.

(8) is solved using the linear least squares which is implemented in many software packages with efficient algorithms (Matlab, Scilab). This method allows a high flexibility, concatenation of different movements, and computation of indicators for the interpretation of the results such as the condition number of the observation matrix and the relative standard deviation.

Condition number of the observation matrix $\boldsymbol{W}$ gives information in the excitation properties of the movements used for identification and sensitivity of the results in the error in the data. A well-conditioned observation matrix is such that $cond(\boldsymbol{W})$ is near 1.

Standard deviations on the estimated values $\sigma_{\hat{X}j}$ are computed using classical and simple results from statistics, considering the matrix $\boldsymbol{W}$ to be a deterministic one, and $\boldsymbol{\rho}$ to be a zero mean additive independent noise, with standard deviation σ_ρ such that:

$$\boldsymbol{C}_{\rho\rho} = E(\rho^T \rho) = \sigma_\rho^2 \boldsymbol{I}_{n_e \times 1}$$

where E is the expectation operator.
An unbiased estimation of σ_ρ is used:

$$\sigma_\rho^2 = \frac{\| \boldsymbol{Y} - \boldsymbol{W}\hat{\boldsymbol{X}} \|^2}{n_e - 3} \tag{9}$$

The covariance matrix of the estimation error and standard deviations can be calculated by:

$$\boldsymbol{C}_{\hat{X}\hat{X}} = E\left((\boldsymbol{X} - \hat{\boldsymbol{X}})(\boldsymbol{X} - \hat{\boldsymbol{X}})^T\right) = \sigma_p^2(\boldsymbol{W}^T\boldsymbol{W})^{-1} \tag{10}$$

$\sigma_{\hat{X}j} = \sqrt{\boldsymbol{C}_{\hat{X}\hat{X}}(j,j)}$ is the i^{th} diagonal coefficient of $\boldsymbol{C}_{\hat{X}\hat{X}}$. The relative standard deviation $\sigma_{\hat{X}j\%}$ is given by:

$$\sigma_{\hat{X}j\%} = 100 \frac{\sigma_{\hat{X}j}}{| \hat{X}_j |} \tag{11}$$

Assuming that $\sigma_{\hat{X}j}$ is the realization of a Gaussian random variable, the 95% confidence interval is $2\sigma_{\hat{X}j}$ and the relative confidence interval is $2\sigma_{\hat{X}j\%}$. Then it is considered that a parameter with a relative confidence interval lower than 10% is well identified, keeping in mind that this is only an indicator based on statistical assumption. The parameters which are not well estimated may be not excited by the identification trajectory, or may have small effect on the dynamic model, so they can be removed from the model [12]. But it is to be noted that this criterion is not deterministic, in particular for parameters with small values, they may be good identified although $\sigma_{\hat{X}j\%}$ is more than 10.

3. Measuring human motion

In order to estimate the human joint dynamics it is necessary to measure the human motion, and from that motion to compute the joint angles and the joint torques.

3.1 Motion capture system

Experiments can be conducted in any equipped motion capture studio. The optical motion capture system used is composed of ten high resolution cameras. Reflective markers are arranged on the subject body as shown Fig.1. The whole system is capable of capturing the reflective marker's position at 30 fps along, if needed EMGs data can be synchronously recorded at 1 KHz.
Markers from the shoulder to the hand, are necessary to record the arm joint movements accurately: they are located as shown Fig.1 and Fig.2 for both sides: one marker on the top of the shoulder (above the acromion), two markers on each side (lateral and medial) of the elbow, two markers on each side of the wrist (ulna's radial side and radius radial side) and one marker on the top of hand. Two more markers, on both hips, are used to define the trunk posture, for a more accurate computation of the inverse kinematics. Consequently 14 reflective optical markers are used.

Fig. 1. The subject equipped with motion capture reflective optical markers and EMG electrodes during experiments

3.2 From markers position to joint angle and joint torque

From the recorded markers positions it is easy to compute the joint angles and the joint torques using the inverse kinematics and inverse dynamics of the musculo-skeletal model. They are computed according [13] where the musculo-skeletal model of the human body is given Fig.2.

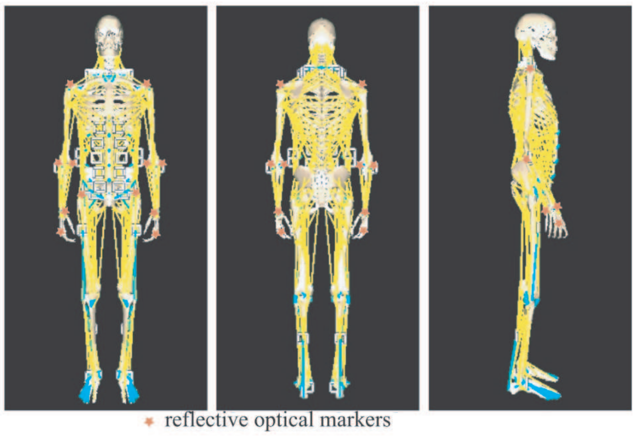

Fig. 2. Musculo-skeletal human model and the positioning of the reflective optical markers

3.3 Required movements for the estimation

A good estimation of dynamics requires a movement where the dynamics to be estimated are excited. This guaranties that the condition number of the observation matrix $\boldsymbol{W}$ is low and close to one. Moreover the movements must be passive. Movements are passive if muscles involved are not neurally activated. EMGs (ElectroMyoGraphies) of the main muscles of the arm must be inspected to insure that muscles are not activated during the movements.
In the aim of medical applications the movements used here are the one performed by a specialist during the diagnosis of neuro-motor diseases such as described in the following section.

4. Medical application of the estimation of the joints dynamics: diagnosis of Parkinson disease

4.1 Medical background

Parkinson disease (PD) is a common neurological disorder which incidence rises after the age of 50, such that about 2% of the elderly in the developed countries are affected. It is due to the a deficiency of dopamine neurotransmitter following neuronal degeneration. Dopamine has an important role in controlling muscle movements, consequently affected people experience trembling, muscle rigidity, slowed motion, difficulty in walking, problems with body balance and coordination, smaller handwriting, drooling. It is slowly progressive and degenerative and it can takes 10 to 15 years from initial diagnosis to later stages. Though earlier stages does not affect much daily life, at the latest stage the affected persons lose the ability to control their movements, making everyday activities hard to manage. The intellect too is affected by the disease. Patients suffer impaired speech, memory and attention problems, dementia, anxiety or depression, or problems with autonomic functions such as blood pressure [14].

The diagnosis of PD is a clinical one: it is based on the patient medical history, observations of his symptoms, and a neurologic examination. There are no confirmatory tests. During the medical diagnosis doctor take special care to the following items:

- Rest tremor of a limb: shaking with the limb at rest,
- Slowness of movement: bradykinesia,
- Rigidity: stiffness, increased resistance to passive movement of the limbs or trunk,
- Poor balance: postural instability.

Table 1. Tests performed by doctors during diagnosis of muscle or neuro-motor diseases, non exhaustive list

	Passive movements
P1	standing in normal position with eyes closed
P2	standing in normal position with open eyes
P3	standing joint feet with open eyes
P4	1 arm lifted and released by doctor back and forward
P4'	both arms lifted and released by doctor back and forward
P5	upper body shaken by doctor [1]
P6	lying on the back forced flexion/extension of hip and knee
	Active movements
A1	normal walk volte-face normal walk
A2	walk on tip toe
A3	walk on heel
A4	lying on the back and rising up
A5	rising from sat position
A6	small jump

[1] It consist in giving rotational impulsion around the vertical axis to the shoulder of the patient and observing the free movements of the arms as shown in Fig.3.

At the moment, the diagnosis of muscles diseases or neuromotor disorder such as Parkinson disease, by doctors, consists in performing a set of tests and examinations on the patient that must reveal by observations the above symptoms, more particularly rigidity and postural instability. Table 1 gives a non-exhaustive list of those tests. They are separated in two types: passive tests and active tests. In the passive tests (P1 to P6) the patient is not moving by himself (no contraction of muscles) but movements are induced by the specialist. While during the active tests (A1 to A6) the patient is asked to perform some movements by himself thus muscles contract.

(a)

(b)

(c)

Fig. 3. Sequences of a movie of the tests performed on the subject by a specialist that is part of the diagnosis test of neuro-muscular diseases such as Parkinson disease: (a) Forward swing of one arm only (P4); (b) Simultaneous forward swing of the two arms (P4'); (c) Body shaking (P5)

4.2 Experimental application

This formalism has first been applied to estimate the dynamics of the human elbow joint [5]. It is now applied to a multi-joint model. As in medical tests passive movements of the upper body and the lower body are usually separate, we have chosen to use two models: one for the upper body and one for the lower body. They can be bring together if a whole joint dynamics estimation is to be performed. The results presented hereafter focus on the upper body.

Each upper limb has two rotational joints: the shoulder and the elbow. Flexion/extension movements only are considered which gives $n_j = 4$. The vector of parameters to estimate consists in the four sets of 3 joint parameters: $\boldsymbol{X} = [k_{ls}\ h_{ls}\ f_{ls}\ k_{rs}\ h_{rs}\ f_{rs}\ k_{le}\ h_{le}\ f_{le}\ k_{re}\ h_{re}\ f_{re}]^T$ where ls denotes the left shoulder, le the left elbow, rs the right shoulder and re the right elbow. The observation matrix is composed of four sub-matrixes corresponding to each joint: $\boldsymbol{W}_{ls}$, $\boldsymbol{W}_{le}$, $\boldsymbol{W}_{rs}$ and $\boldsymbol{W}_{re}$. For each joint the condition number is computed to give a joint to joint information.

The experiments are conducted as described in section 4.1: a valid subject is equipped with optical markers and a muscle diseases practitioner performs a full medical diagnosis check-up such has shown in Table 1 and in Fig.3. Movements, as well as EMGs are captured, even though EMGs are not used for estimation, but just to ensure the passivity of the movements. Normalized EMGs records given Fig.4

are about 1% for both Biceps and Triceps which shows that muscles are not activated and consequently movements are passive.

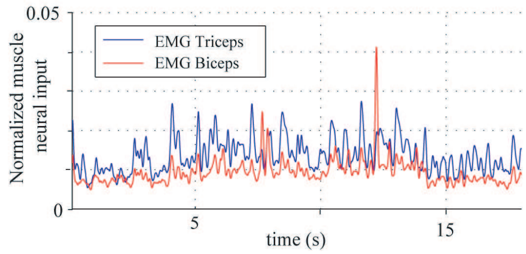

Fig. 4. Level of normalized (0<u<1) neural input of the Biceps and the Triceps during the medical diagnosis

From common sense it is obvious that only movement P4 and P5 are relevant for the estimation of the upper limb joints dynamics and can guaranty for a low condition number of the observation sub-matrixes. The P4 test used for estimation is the swing of the left arm only (the right arm almost doesn't move), test P4' is used for the estimation of both sides dynamics as both arms swing and the P5 test is a regular shake of the body. The estimation is carried out using the concatenation of 4 tests P4, 2 tests P4' and two tests P5 respectively. Obtained results are presented in table 2. The parameter o is an estimated offset in order not to consider the rest position of the arm q_j^r.

TABLE 2. EXPERIMENTAL RESULTS OF THE MULTI-JOINT ESTIMATION OF THE HUMAN UPPER LIMBS DYNAMICS

test:	P4		P4'		P5	
par	$\hat{\boldsymbol{X}}$	$\sigma_{\hat{X}_j}\%$	$\hat{\boldsymbol{X}}$	$\sigma_{\hat{X}_j}\%$	$\hat{\boldsymbol{X}}$	$\sigma_{\hat{X}_j}\%$
$cond(\boldsymbol{W}_{ls})$		**6.06**		**6.09**		**5.67**
k_{ls}	17.11	1.55	15.51	2.64	17.39	1.72
h_{ls}	0.64	10.68	0.14	88.49	0.75	15.28
f_{ls}	-0.27	41.28	-0.08	131.21	0.22	55.30
o_{ls}	-1.27	6.64	-4.65	2.85	-2.72	2.82
$cond(\boldsymbol{W}_{le})$		10.40		12.86		9.59
k_{le}	8.62	2.08	7.04	1.93	5.79	2.21
h_{le}	0.23	22.34	0.22	15.55	0.21	16.16
f_{le}	-0.07	63.27	-0.04	56.35	0.01	299.16
o_{le}	-7.85	1.88	-7.08	1.68	-6.37	1.91
$cond(\boldsymbol{W}_{rs})$		28.03		**6.36**		**6.17**
k_{rs}	9.40	3.23	14.85	3.04	16.21	3.08
h_{rs}	0.40	41.61	0.06	218.19	1.08	14.48
f_{rs}	0.06	26.61	-0.11	101.04	-0.08	217.28
o_{rs}	-1.20	4.19	-4.78	3.22	-3.28	3.94
$cond(\boldsymbol{W}_{re})$		25.20		12.95		8.65
k_{re}	1.04	6.40	6.44	2.45	4.45	3.36
h_{re}	-0.11	40.25	0.34	11.12	0.35	11.32
f_{re}	-0.02	27.81	-0.04	66.81	0.01	373.05
o_{re}	-1.79	3.10	-6.32	2.07	-4.55	2.64

In the first place, it is necessary to have a look at the condition number of the observation matrix $\boldsymbol{W}$ for each joint to evaluate the possibility of estimating the parameters with the given movements. With the test P4 the condition number of the left side is low while for the right side it is very high for both joints and consequently parameters of the right side are not estimated properly and those results are not considered hereafter. It is an obvious result considering that the right arm doesn't move. Moreover the left elbow have a poor condition number too which means that its dynamics is poorly excited. For test P4' both shoulders dynamics are excited but same remark as above concering the elbows. For the test P5 the condition number of the shoulders is good, while it is being bad for the elbows. One can note that the elbow dynamics using those movements is hard to excite.

Let us now consider the corresponding relative standard error $\sigma_{\hat{X}_j}\%$ computed for each estimated parameter according to (11) in the cases of well-conditioned systems. In every cases the relative standard error of the stiffness parameter is lower than 10 which means that stiffness is properly estimated. Considering viscosity and friction parameters, the relative standard error is high, though the parameters estimated are very low. One can hardly conclude on the real value, but one can only say that both elbow and shoulder joints have poor friction and viscosity during passive movements. Offset o are also well estimated and correspond to $-k_j q_j^r$ in (3).

Finally, let us consider validation figures given Fig.5 to 7 where the joint torque measured $\boldsymbol{Y}$ (blue thick line) and the joint torque estimated from joint angle and elbow dynamics: $\boldsymbol{W}\hat{\boldsymbol{X}}$ (red thick dash line) are compared. Error $\boldsymbol{Y} - \boldsymbol{W}\hat{\boldsymbol{X}}$ is also given (thin black line). Direct validations (same movement used for estimation and validation) are given Fig.5 and 6 for respectively test P4'and P5. Cross validations (different movement for the estimation and the validation) of the results obtained with test P4 are given in Fig.7. Both validations give low error between the measured torque angle and the estimated one from the joint dynamics identified which confirms the interpretation of the obtained results.

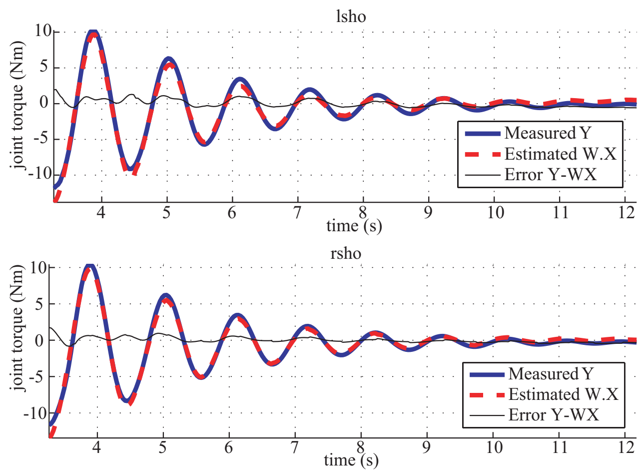

Fig. 5. Direct Validation of the results for the left and right shoulders using test P4', left shoulder (top), right elbow (bottom)

5. CONCLUSION

An original and simple solution for in-vivo estimation of passive multi-joint dynamics of the human body has been proposed. It is based on the use of the kinematics and dynamics computations of musculo-skeletal model of the human body coupled with a motion capture studio. The

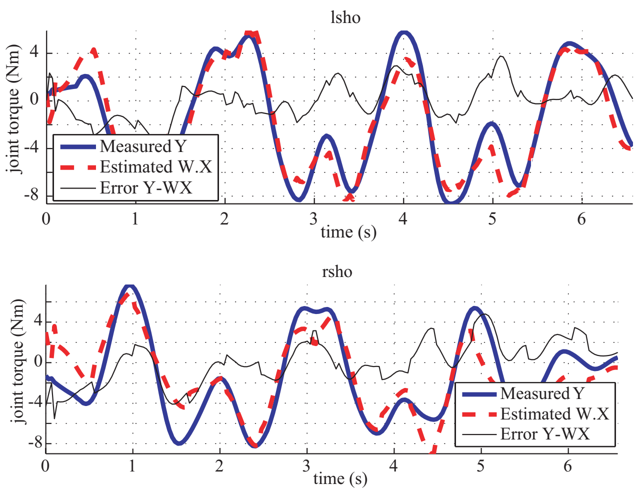

Fig. 6. Direct Validation of the results for the left and right shoulders using test P5: left shoulder (top), right shoulder (bottom)

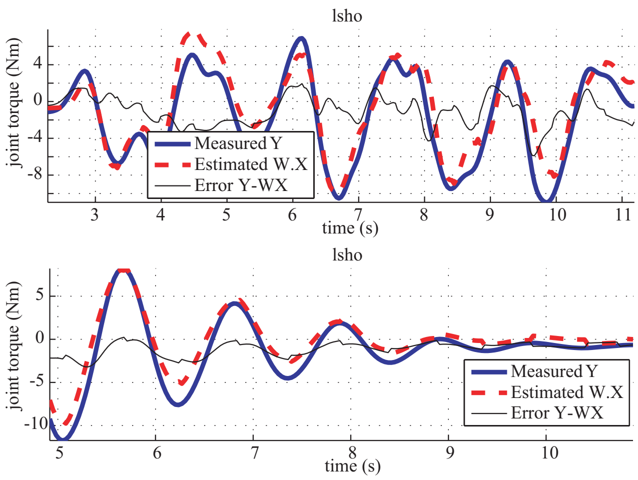

Fig. 7. Cross validation of the results obtained for the left shoulder using test P4: validation with test P5 (top), validation with test P4' (bottom)

joint dynamics is linear in the stiffness, viscosity and friction and such model can be discussed. The dynamic model sampled along an appropriate passive movement gives an over-determinate system that is solved with least squares method. Experimental results obtained with medical diagnosis show that the estimation is possible, but movement could be enhanced to excite more the dynamics of the elbow joints and to reveal the viscosity and friction parameters. Such enhancements can be made by simulating the human body during several passive movements using different initial configurations. This method presents the great advantage to have a very easy roll-out for applications by neuro-motor diseases and muscle diseases specialists. As the passive behavior of joints is intrinsically linked to the muscles and the neural input: stiffening of muscles such as occurs in Parkinson disease implies global stiffening of the joint these results provide a good quantifier of the evolution of the disease. This method can also be used to design more relevant diagnosis tests to estimate the joint dynamics and help specialist in enhancing their diagnosis. Future works mainly concern the enhancements of the movements and the application of the method to a wider panel of subjects including people suffering from neuro-motor diseases, and to the joints of the lower limbs: ankle, knee and hip.

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References

[1] S.L. Delp and J.P. Loan, "A software system to develop and analyze models of musculoskeletal structures," *Computers in Biology and Medicine*, vol. 25, pp. 21–34, 1995.

[2] D.G. Thelen, F.C. Anderson, and S.L. Delp, "Generating dynamic simulations of movement using computed muscle control," *Journal of Biomechanics*, in press.

[3] 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 *Proceedings of the 2nd International Symposium on Adaptive Motion of Animals and Machines*, Kyoto, Japan, March 2003.

[4] K. Tahara, Z.W. Luo, T. Odashima, M. Onishi, S. Hosoe, and Kato A., "Dynamic control and simulation of human musculo-skeletal model," in *Proc. of SICE Annual Conference in Sapporo*, Japan, August 2004, pp. 2395–2398.

[5] G. Venture, K. Yamane, and Y. Nakamura, "In-vivo estimation of the human elbow joint dynamics during passive movements based on the musculo-skeletal kinematics computation," in *IEEE/Int. Conf. on Robotics and Automation*, Orlando, USA, May 2006, p. to be published.

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

[7] G. Venture, W. Khalil, M. Gautier, and P. Bodson, "Parametric identification of a car dynamics," in *IFAC Symposium on System Identification, Rotterdam, Netherlands*, August 2003.

[8] P. Aarnio, K. Koskinen, and S. Salmi, "Simulation of the hybtor robot," in *Proc. of the 3rd Int. Conf. on Climbing and Walking Robots, Madrid, Spain*, Professional Engineering Publishing Ltd, Ed., 2000, pp. 267–274.

[9] M.W. Hannan and I.D. Walker, "Kinematics and the implementation of an elephantŠs trunk manipulator and other continuum style robots," *Journal of Robotic Systems*, vol. 20, no. 2, pp. 45–63, 2003.

[10] S. Stroeve, "Learning combined feedback and feedward control of a musculoskeletal system," *Biol. Cybern.*, vol. 75, pp. 73–83, 1996.

[11] M. Gautier, "Dynamic identification of robots with power model," in *Proc. Int. Conf. on Robotics and Automation, Albuquerque, USA*, 1997, pp. 1922–1927.

[12] C. Pressé and M. Gautier, "New criteria of exciting trajectories for robot identification," in *Proc. IEEE Int. Conf. on Robotics and Automation, Atlanta*, 1993, pp. 907–912.

[13] K. Yamane, T. Kuroda, and Y. Nakamura, "High-precision and high-speed motion capture by combining heterogeneous cameras," in *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems*, Sendai, Japan, September–October 2004, pp. 279–286.

[14] C. Marsden, *Movement Disorders*, textbook of medecine edition, 1987.