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In-vivo Estimation of the Human Elbow Joint Dynamics during Passive Movements Based on the Musculo-skeletal Kinematics Computation

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***Abstract*— Human upper limb joints dynamics is very important in the fields of humanoid robotics, medical robotics as well as medical research. To make human-like passive movements of the arms when walking humanoid robot arms must have similar dynamics to the human arms, even more if this arm is to be used as a prosthesis. Moreover medical diagnosis of muscle or neuro-motor diseases are based on a visual qualitative estimation of joint passive stiffness. There is a pressing need in human body dynamics characterization and especially in subject specific characterization. In this paper a solution to estimate in-vivo the passive dynamic of the arm joint is proposed. It is based on the use of the musculo-skeletal description of the human body and its kinematics computation. The linear passive joint dynamics: stiffness, viscosity and friction, is then estimated with least squares method. Acquisition of movements both designed for estimation or from medical diagnosis check-up, are achieved with motion capture studio only (no pain, no distress on subject). Experimental results for three valid subject are given.**

***Index Terms*— joint dynamics, inverse dynamics, muscculo-skeletal human model, motion capture**

I. INTRODUCTION

Due to advances in humanoid robotics and more particularly in the development of artificial muscles, robots are getting closer to human. Although it is still difficult to design and control robots with smooth, realistic movements and behavior, it is an important issue to facilitate human-robot interaction [1]. Researches on walking human-like robots focusing on the movements of the legs only have been very successful, nevertheless still few walking patterns use the movements of the trunk [2] and the arms [3]. Even though, to make a realistic human-like walk, arms must have free movements: the robot's arms - shoulder and elbow joints - must swing by themselves. For that they need to have dynamic properties close to the real human arms not to swing too much and become dangerous, nor to stand still and gives impression of rigidness. Moreover, stiffness performances of the system must guaranty that stability is kept during the walk [4] and free joint movements can help in stabilizing [3]. Consequently dynamic properties of both the human body and the robot must be accurately known. In the same way, very promising bio-medical applications of robotics such as design of prosthesis must accurately fit with the patient body dynamics to make it comfortable and easy to use. Bio-mechanical literature gives some average parameters for some class of people [5], [6], but subject specific parameters estimation is not commonly used. Furthermore, bio-mechanical or biological in-vivo problems are usually solved using expensive or painful experiments which make subject very reluctant to volunteer. Finally an other important reason to focus research on the human upper limb joint dynamics is to give medical researchers on muscles and neuro-motor diseases a quantification of joint rigidity of people suffering from those diseases. Medical diagnosis check-up gives only visual appreciation of rigidity of the body joints and for people suffering from slow evolutional neuro-motor diseases or Parkinson disease it is difficult to have a clear appreciation of occurring changes at each check up.

As a matter of fact this paper proposes an original method to estimate in-vivo the human joint dynamics for passive movements, painless and without distress, with only a motion capture studio. This method is widely applicable to all the human limbs joints. For medical applications purpose it is here applied to the elbow joint. It is based on the use of a musculo-skeletal dynamics computation and a linear modelling of the human elbow joint dynamics: stiffness, viscosity and friction. Inertial parameters of the arm must previously be estimated using multi-body description of the arm and linear property of the inverse dynamic model in the inertial parameters [7]. The sampled linear over-determinate system obtained along a movement with good excitation properties that is designed for that purpose or from medical diagnosis, is solve with least squares method. Standard deviation is computed statistically to interpret the obtained results. Experimental setup is described and experimental results for several subjects are given and discussed.

II. MODELLING OF THE HUMAN BODY

Powerful robotics formalisms, such as Modified Denavit Hartenberg formalism [7], allow to describe systems as multi-body systems linked by joints. Such description has been applied to manipulator robots, mobile robots [8], [9] as well as biologically inspired robots [10] 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 [11], [12]. Those modelling allow to compute easily the inverse kinematics as well as the inverse dynamics for the whole human body with 366 muscles driving a skeleton with 155 degrees of freedom (DOF).

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

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:

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

- $\boldsymbol{G}_j(\boldsymbol{q})$ 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:

$$\Gamma_j^e = k_j(q_j - q_j^r) \tag{3}$$

    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:

$$\Gamma_j^v = h_j \dot{q_j} \tag{4}$$

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

$$\Gamma_j^f = f_j sign(\dot{q_j}) \tag{5}$$

As mentioned above the inertial parameters $\boldsymbol{D}_P$ are known. They can be estimated from previous experiments requesting force sensors or torquemeter, or scaled from literature's available parameters [5]. 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:

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

where the left side is known: inertial effects of the arm, 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:

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

- $\boldsymbol{X}$ 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 [7], [13].
The dynamic model (6) is sampled along an exciting movement. All the n_e samples give a linear system of equations:

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

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) can be solved using the least squares which is implemented in many software packages with efficient algorithms (Matlab, Scilab). 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:

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

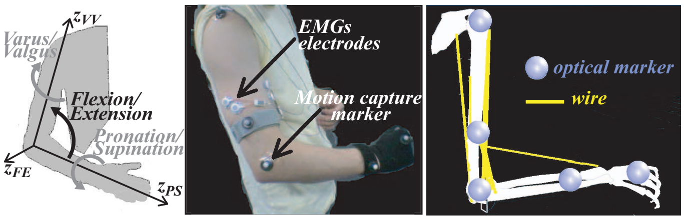

Fig. 1. The elbow joint degrees of freedom (left), the experimental set-up of the subject (center) and detail of the musculoskeletal model of the elbow joint (right)

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 [14]. 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.

III. Experimental setup - Application to the elbow joint

Such formalism is thus used for the human arm and the elbow joint. The elbow joint has 2 main rotational degrees of freedom of about 180° range for each that allow the hand to move widely as shown in Fig.1.

This paper focuses on flexion/extension (F/E) of the elbow joint, which correspond to the rotation around $\boldsymbol{z_{FE}}$ axis in Fig.1. General equation of the inverse dynamic model given by (1) is applied to the elbow joint flexion extension as a one degree of freedom joint with elasticity ($n_j = 1$). The vector of parameters to estimate is then $\boldsymbol{X} = [k\ h\ f]^T$.

In order to achieve the estimation of the human joint elbow dynamics in-vivo, with no pain and distress to the subject, and to make the methods widely applicable for medical diagnosis, the only required equipment is a motion capture studio.

A. 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.
Five markers, from the shoulder to the hand, are necessary to record the elbow joint movements accurately. Three more markers, on the opposite shoulder and both hips, are used to define the trunk posture (Fig.2), for a more accurate computation of the inverse kinematics.

B. From markers position to joint angle

The inverse kinematics model is computed by the musculo-skeletal model of the human body given Fig.2. For computing

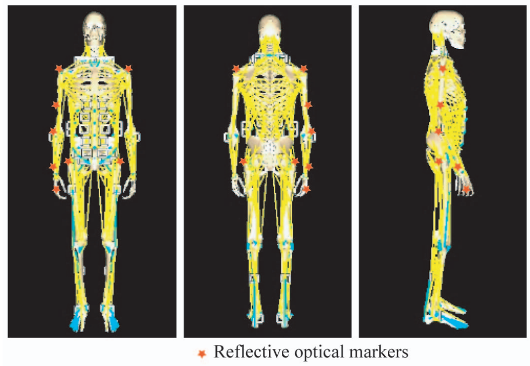

Fig. 2. Musculo-skeletal human model

the joint angles q from markers position data obtained by the optical motion capture system an inverse kinematics algorithm, similar to UTPoser algorithm [15] is used. It computes a natural posture that satisfies the given marker positions. The elbow joint, which is usually modelled as one degree of freedom joint, is modelled as three degrees of freedom spherical joint for realistic representation.

C. Movements of sufficient excitation for the estimation

A good estimation of dynamics requires a movement where all the dynamics to be estimated are excited in order that the condition number of $\boldsymbol{W}$ is low and close to one. For the first test movements are chosen for their good properties on the dynamics to be estimated. It is said that to estimate the passive elbow joint dynamics it is necessary to have a wide movement with no external force applied. For this the subject is seated, shoulder maintained at 90° to the back and forearm is vertical at rest. The forearm is lifted then released by an operator as shown in Fig.3. Such a movement is appropriated to estimation but somehow it can be difficult to be executed by people with disease or getting old, moreover it is not a typical diagnosis movement for medical doctors. Consequently the second test has been achieve by a medical doctor and consist in giving rotational impulsion around the vertical to the shoulder of the patient and observing the free movements of the arms (Fig.4).

Movements are passive if muscles involved are not neurally activated. EMGs (ElectroMyoGraphies) of the main muscles of the arm are inspected to insure that muscles are not activated during the movements. Normalized records are given Fig.5 for the Biceps and the Triceps during the medical diagnosis. The neural activity is about 1% for each muscle which shows that muscles are not activated.

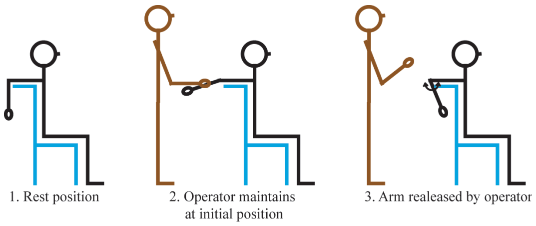

Fig. 3. Experimental process: exciting movement for the joint elbow dynamics: patient seated, operator helps conducted the experiments

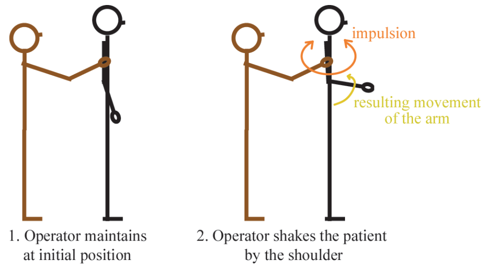

Fig. 4. Experimental process: movements achieved during medical diagnosis, patient standing, operator giving impulsion to him by the shoulders

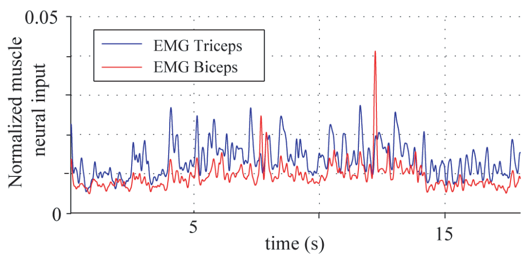

Fig. 5. Level of normalized (0<u<1) neural input of the Biceps and the Triceps during the medical diagnosis

IV. Experimental Identification of the Elbow Joint Dynamics

To conduct the experiments in the aim of the estimation of the human elbow joint dynamics three volunteers valid subjects are equipped with optical markers and are taught about the first experimental process shown Fig.3 (Section III-C). An operator is helping to perform the movement as relaxed as possible. The movement is repeated and recorded four to six times. For each subject, estimation is carried out with concatenation of all the movements recorded to give about 1100 samples. Condition numbers of the observation matrix $\boldsymbol{W}$ is respectively 2.91, 3.11 and 3.08 for each subject, which is close to one and proves the good dynamics of the tests. Joint angle is computed from the inverse kinematics as above and inverse dynamic model (8) is computed and solved with least squares method. Standard deviation is computed following (11). Obtained results are given in table I.

TABLE I

Results of the estimation with designed movements

parameter	unit	estimated $\hat{\boldsymbol{X}}$	$\sigma_{\hat{X}j}\%$
		subject 1	
Stiffness k	Nm/rad	2.609	0.29
Viscosity h	Nms/rad	0.049	7.47
Friction f	Nm	-0.017	25.38
		subject 2	
Stiffness k	Nm/rad	2.238	0.25
Viscosity h	Nms/rad	0.029	9.39
Friction f	Nm	-0.012	20.9
		subject 3	
Stiffness k	Nm/rad	2.166	0.24
Viscosity h	Nms/rad	0.022	13.70
Friction f	Nm	-0.003	68.07

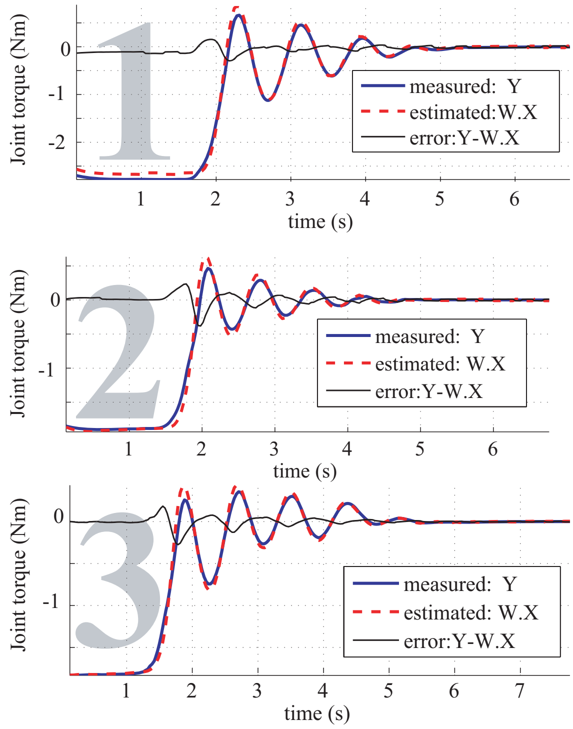

Fig. 6. Direct validation for the three subjects

Results given above show that for the three subjects the stiffness k of the elbow joint can be estimated with very good accuracy according to the low value of the relative standard deviation $\sigma_{\hat{X}j}\%$. The joint viscosity is also estimated for subject 1 and 2 with good accuracy: $\sigma_{\hat{X}j} < 10$, though for subject 3 the value of the parameter is lower and then $\sigma_{\hat{X}j}\% > 10$ but still low which allow to assume that estimation is good. For friction the value estimated is very low consequently the relative standard deviation $\sigma_{\hat{X}j}\% > 10$, it is then impossible to concluded from analyzing the relative standard deviation. According to the similarity of the results for the three subject it is to be noted that friction in joint elbow is very low: less than 5% of the joint torque.

Fig. 7. Sequence 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

Results obtained can be compared to literature which gives average data with few details about gender, size, age or condition and it is to be noted that the standard size and mass of the subject in literature are different from our subjects. Average stiffness of elbow joint given by Stroeve in [16] is 1.5 Nm/rad which confirmed the obtained results. Average viscosity is 0.2 Nms/rad which can be discussed from the differences noted above and that viscosity term includes the viscosity term due to co-activated muscles.

Finally, Fig.6 gives the joint torque measured $\boldsymbol{Y}$ and the joint torque estimated from joint angle and elbow dynamics: $\boldsymbol{W}\hat{\boldsymbol{X}}$. The test used is random test that as been performed on the subject. Error $\boldsymbol{Y} - \boldsymbol{W}\hat{\boldsymbol{X}}$ (black dotted line) is low for all the three subjects.

Identification of the elbow joint dynamics during the medical diagnosis is then tested. A muscle diseases practitioner has performed a medical diagnosis check-up on subject 1 and 2 as shown Fig.7. Movements, as well as EMGs (Fig.5) were captured. Some other passive movements during the diagnosis were also captured for further cross validation. As previously, recorded movement is used for the estimation of the elbow joint dynamics. Condition number of observation matrix $\boldsymbol{W}$ is 2.3 for less than 700 samples for subject 1 and 2.2 for less than 500 samples for subject 2. Results are given in table II, direct validation and cross validations for two passive movements not used for the estimation are given in Fig.8 for subject 1 and Fig.9 for subject 2.

According to the correspondent relative standard error, the stiffness of the elbow joint is estimated with very good accuracy. However viscosity and friction have high relative standard error: $\sigma_{\hat{X}j}\% > 20$, thus are poorly estimated. Nevertheless they are in the same range as the one estimated with the first test and validation as well as cross validation give low error between the measured torque angle and the estimated one from the joint dynamics identified: 8 and 9. The estimation with the medical diagnosis movement is possible, but movement could be enhanced to excite more the viscosity and friction parameters.

TABLE II

RESULTS OF THE ESTIMATION USING MEDICAL DIAGNOSIS MOVEMENTS

parameter	unit	estimated $\hat{\boldsymbol{X}}$	$\sigma_{\hat{X}j}\%$
		subject 1	
Stiffness k	Nm/rad	2.951	0.179
Viscosity h	Nms/rad	0.031	21.7
Friction f	Nm	-0.015	30.1
		subject 2	
Stiffness k	Nm/rad	2.353	0.31
Viscosity h	Nms/rad	0.028	23.19
Friction f	Nm	-0.013	47.62

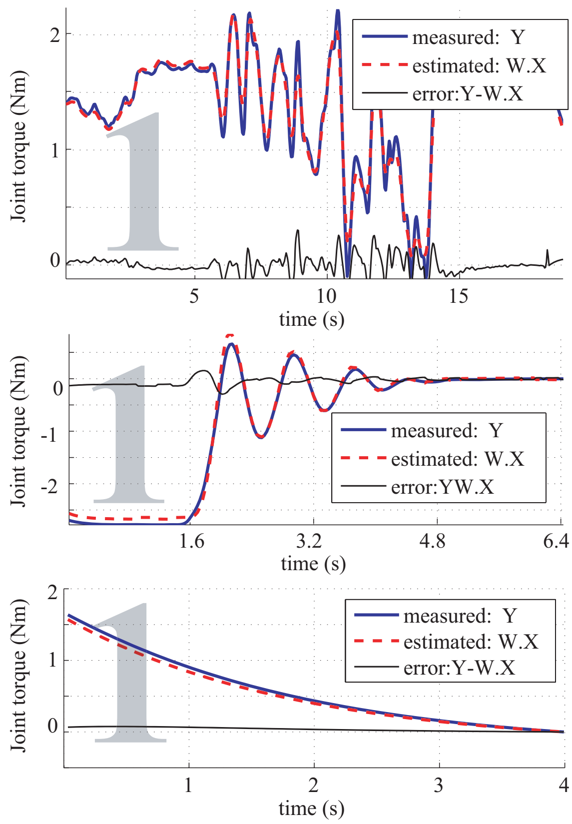

Fig. 8. Validation of the results estimated with the medical diagnosis test, Subject 1: direct validation (top), cross validation (middle and bottom)

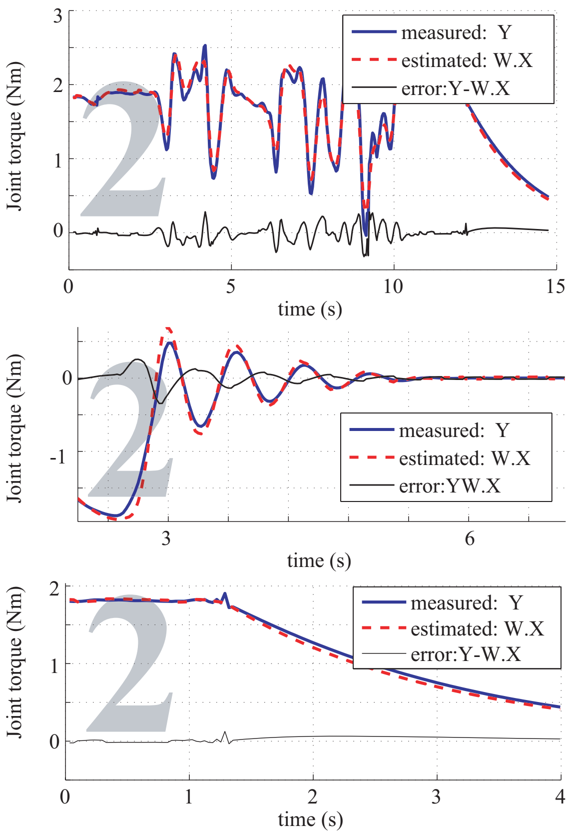

Fig. 9. Validation of the results estimated with the medical diagnosis test, Subject 2: direct validation (top), cross validation (middle and bottom)

V. Conclusion

An original solution for in-vivo estimation of passive joint dynamics of the human body is proposed in this paper. It is based on the use of the kinematics computation of musculo-skeletal model of the human body coupled with a motion capture studio. The joint dynamics is linear in the stiffness, viscosity and friction. The dynamic model sampled along an exciting passive movement gives an over-determinate system that is solved with least squares method. Experimental results obtained for three different people performing the designed movement for that purpose show that estimation is successful. Interpretation is confirmed by the low value of the standard deviation for stiffness and viscosity, and by the low relative error of estimated joint torque from identified dynamics. Stiffness results are also corresponding with literature data. Results obtained with medical diagnosis show that estimation is also possible, though the movements could be enhanced to excite more the concerned joint dynamics. Such results are very important to design human-like robots, to make realistic and foreseeable movements. They are also important for bio-robotics applications to make and tune prosthesis, as well as for neuro-motor diseases and muscle diseases researchers. 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. This method will be used to the upper limbs joints using the multi-body description. Thus wrist, elbow and shoulder dynamics of both side will be simultaneous estimated. Weighting procedure could be used for each joint to ensure a better estimation and lower relative standard deviation.

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