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Parameters Estimation of the Actuator used in Haptic Interfaces: Comparison of two Identification Methods

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Abstract - In advanced motor control systems, an accurate knowledge of motor parameters is essential in order to achieve good performances. Some of these parameters, such as stator resistances, are sometimes given by constructors, but they vary according to the operating conditions. This paper presents and compares two parameter identification methods of an actuator used in haptic interfaces which, in this case, is a Permanent Magnet Synchronous Machine (PMSM). Using these methods, the electrical parameters of the PMSM can be determined during different operating conditions. Physical parameters estimation of a dynamic 4-parameter model is performed on the one hand, using an Output Error identification method based on a Non Linear Programming algorithm and on the other hand, using an identification method based on Least-Squares techniques and inverse models.

I. INTRODUCTION

A haptic interface is a computer device, which enables its user to interact with the image in a virtual reality application or model, through the sense of touch. Users can experience feelings of touch and movement thanks to this technology that optimizes human communication with machines and intensifies a human's immersion in a virtual world. Such systems are in growing demands for applications such as mobile robotics, force feedback remote-control systems for extreme environment, man-machine interaction and training in professional operating procedures [1][2]. They consist of an articulated mechanical structure with motors and position sensors, as well as embedded electronics. The user holds the end-point of the structure in his hand, and can move it around, both in the real and in the virtual world on the computer screen. Whenever his virtual hand makes contact with a digital object, a force value is sent to the motors, which simulates a real contact.

The proposed system (Fig. 1) is based on brushless Permanent Magnet Synchronous Machines (PMSM). In order to obtain a torque regulation with the best dynamic behavior, the best stiffness and transparency of the system [3] and without ripples, an accurate dynamic model of the system and the knowledge of the electrical parameters values are required.

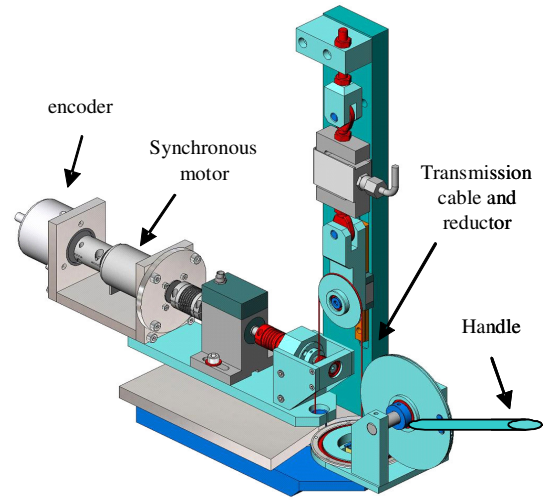


Fig. 1. Experimental single degree of freedom haptic interface.

The paper is divided as follows. Section II presents the dynamic model of the actuator (PMSM) used in the studied haptic interface. Section III describes the principle of the two identification methods used to estimate the electrical parameters of the PMSM: Least Squares techniques and inverse models on the one hand and Output Error method and Marquardt algorithm on the other hand. Section IV compares both methods in simulation and presents parameter estimation results in deterministic and stochastic cases. Section V presents the experimental protocol for data measurements as well as the experimental estimation results obtained with the two identification methods.

II. ELECTRICAL MODEL OF THE ACTUATOR

The PMSM electrical model in the Park synchronous reference frame [4] is described in (1) and (2). V_d , V_q , i_d and i_q are respectively the direct and quadrature axis voltage and current components and ϕ_f is the permanent magnet flux.

The synchronous (d , q) reference frame is the natural choice for the present analysis, because all periodic quantities

are constant in steady state and the model is linear at constant speed.

The electrical PMSM model in (d, q) reference frame is given by the following equations:

$$\begin{cases} \phi_d = L_d \cdot i_d + \phi_f \\ \phi_q = L_q \cdot i_q \end{cases} \quad (1)$$

$$\begin{cases} V_d = R_s i_d + L_d \frac{di_d}{dt} - \omega L_q i_q \\ V_q = R_s i_q + L_q \frac{di_q}{dt} + \omega L_d i_d + \omega \phi_f \end{cases} \quad (2)$$

The electrical parameters to identify are the stator windings resistance R_s , the stator direct and quadrature axis inductances L_d and L_q and the permanent flux ϕ_f .

III. TWO IDENTIFICATION METHODS PRINCIPLE

A. Least-squares and inverse model method

1. Principle

Generally, the ordinary Least-Squares (L.S) technique is used to estimate the minimum dynamic parameters solving an overdetermined linear system obtained from a sampling of the dynamic electrical model, along a given trajectory (z, \dot{z}, \ddot{z}) [5] [6], where z is a $rx2$ vector, which represents here the current vector $[i_d \ i_q]^T$ and (\dot{z}, \ddot{z}) its derivatives.

$\underline{\theta}$ is the minimum parameter vector to identify, Y the measurements vector, W the observation matrix (or regressor) and ε the vector of input errors. The system is described as follows:

$$Y = W \cdot \underline{\theta} + \varepsilon \quad (3)$$

The electrical model of the PMSM given in (2) can be written as the following linear inverse model:

$$Y = W \cdot \underline{\theta} \quad (4)$$

where:

$$\begin{cases} Y = \begin{bmatrix} V_d \\ V_q \end{bmatrix} & \underline{\theta} = \begin{bmatrix} R_s \\ L_d \\ L_q \\ \phi_f \end{bmatrix} \\ W = \begin{bmatrix} i_d & \frac{di_d}{dt} & -p \cdot \Omega \cdot i_q & 0 \\ i_q & \frac{di_q}{dt} & p \cdot \Omega \cdot i_d & p \cdot \Omega \end{bmatrix} \end{cases} \quad (5)$$

The L.S solution $\hat{\underline{\theta}}$ minimizes the 2-norm of the input errors vector ε . The unicity of $\hat{\underline{\theta}}$ depends on the rank of the observation matrix W .

W is a rxK full rank and well conditioned matrix, obtained by tracking an exciting trajectory, where K is the number of samples.

Standard deviations σ_ε are estimated using classical and simple results from statistics. The matrix W is supposed deterministic and ε a zero-mean additive independent noise, with a standard deviation such as:

$$C_{\varepsilon\varepsilon} = E(\varepsilon^T \varepsilon) = \sigma_\varepsilon^2 I_r \quad (6)$$

where E is the expectation operator and I_r , the rxr identity matrix. An unbiased estimation of σ_ε is:

$$\hat{\sigma}_\varepsilon^2 = \frac{\|Y - W \hat{\underline{\theta}}\|^2}{r - K} \quad (7)$$

The covariance matrix of the standard deviation is calculated as follows:

$$C_{\hat{\underline{\theta}}\hat{\underline{\theta}}} = E\left[(\underline{\theta} - \hat{\underline{\theta}})(\underline{\theta} - \hat{\underline{\theta}})^T\right] = \sigma_\varepsilon^2 (W^T W)^{-1} \quad (8)$$

where $\sigma_{\hat{\theta}_i}^2 = C_{\hat{\underline{\theta}}\hat{\underline{\theta}}}$ is the i^{th} diagonal coefficient of $C_{\hat{\underline{\theta}}\hat{\underline{\theta}}}$.

$\sigma_{\hat{\theta}_i}$ represents the standard deviation of the parameter θ_i .

It allows the definition of a confidence interval of the parameter estimation, equal for instance to $\pm 3 \cdot \sigma_{\hat{\theta}_i}$.

However, in practice, W is not deterministic. This problem can be solved by filtering the measurement matrix Y and the columns of the observation matrix W as described in [7] [8].

2. Data filtering

Vectors Y and z are samples measured during an experimental test. The derivatives \dot{z} and \ddot{z} are obtained without phase shift using a centered finite difference of the vector z . The choice of the cut-off frequency ω_f of the lowpass filter is very sensitive because the filtered data $(z_f, \dot{z}_f, \ddot{z}_f)$ must be equal to the vector (z, \dot{z}, \ddot{z}) in the range $[0, \omega_f]$, in order to avoid distortion in the dynamic regressor. The filter must have a flat amplitude characteristic without phase shift in the range $[0, \omega_f]$, with the rule of thumb $\omega_f > 10 \cdot \omega_{dyn}$, where ω_{dyn} represents the dynamic frequency of the system.

Considering an off-line identification, it is easily achieved with a non-causal zero-phase digital filter by processing the input data through an IIR lowpass butterworth filter in both the forward and reverse direction. The measurement vector Y is also filtered, thus, a new filtered linear system is obtained:

$$Y_f = W_f \cdot \underline{\theta} + \varepsilon_f \quad (9)$$

As there is no more signal in the range $[\omega_f, \omega_s / 2]$, where ω_s is the sampling frequency, vector Y_f and matrix W_f are resampled at a lower rate after lowpass filtering, keeping one sample over n_d samples, in order to obtain the final system to identify:

$$Y_{fd} = W_{fd} \cdot \underline{\theta} + \varepsilon_{fd} \quad (10)$$

$$\text{with } n_d = 0.8 \frac{\omega_s}{2 \cdot \omega_f} \quad (11)$$

To sum up, the L.S and inverse model method presents some advantages: the method is simple and is not time consuming since the convergence is obtained after only one iteration. However, the model to identify must be linear in respect to parameters $\underline{\theta}$.

As generally, physical systems can be described by differential equations, a solution to make the model linear in respect to parameters is to use inverse model and to calculate the derivatives of the measured signals. Thus, the integration of the differential equations is of no use and the problem of the initial conditions of states and parameters does not exist.

However, the derivatives must be obtained without phase shift by using for instance a central algorithm differentiation of the vector z . Knowing that z may be disturbed by high frequency noises, which will be amplified during the derivation, a lowpass filter with an order greater than 2, is used in order to eliminate these noises, as described in the previous section.

Thus, using inverse model and LS technique seems to be sensitive to measurement noises and the estimation results may be biased. The bias may be amplified if the filtering procedure is not suitable. Moreover the L.S method is known to be sensitive to modelling error.

B. Output Error method

1. Model of the system

Let's consider a general state-space representation:

$$\dot{\underline{x}} = \underline{g}(\underline{x}, \underline{\theta}, u) \quad (12)$$

$$y = f(\underline{x}, \underline{\theta}, u) \quad (13)$$

A SISO (Single Input Single Output) system is considered afterwards to simplify the writing of equations. $u(t)$ is the input and a predicted output $\hat{y}(t)$ is obtained after numerical simulation of the state-space model:

$$\hat{y}(t) = f(u(t), \hat{\underline{\theta}}) \quad (14)$$

where $\hat{\underline{\theta}}$ is an estimation of $\underline{\theta}$.

The PMSM state-space model is given by the following equations:

$$\frac{d}{dt} [X] = [A][X] + [B][U] \quad (15)$$

$$\text{with } [A] = \begin{bmatrix} -\frac{R_s}{L_d} & p \cdot \Omega \cdot \frac{L_q}{L_d} \\ -p \cdot \Omega \cdot \frac{L_d}{L_q} & -\frac{R_s}{L_q} \end{bmatrix} \text{ and } [B] = \begin{bmatrix} \frac{1}{L_d} & 0 \\ 0 & \frac{1}{L_q} \end{bmatrix}$$

and where $[U] = [V_d, (V_q - p \cdot \Omega \cdot \phi_f)]^t$ and $[X] = [i_d, i_q]^t$.

2. Minimisation of the quadratic criterion

Let's assume the we have measured K values of the output $y^*(t)$, such as, u_k, y_k^* are respectively the k^{th} sample of the system input and output, with $t = k T_e$ and where T_e is the sampling period.

The output prediction error is defined as:

$$\varepsilon(t) = y^*(t) - \hat{y}(u(t), \hat{\underline{\theta}}) \quad (16)$$

The optimal value of $\hat{\underline{\theta}}$ is obtained by minimisation of the following quadratic criterion :

$$J = \sum_{k=1}^K \varepsilon_k^2 = \sum_{k=1}^K (y_k^* - \hat{y}_k(u_k, \hat{\underline{\theta}}))^2 \quad (17)$$

Because $\hat{y}(t)$ is non linear in respect to $\hat{\underline{\theta}}$, a Non Linear Programming (NLP) technique is used to estimate iteratively $\hat{\underline{\theta}}$:

$$\underline{\theta}_{i+1} = \underline{\theta}_i - \left\{ [J''_{\theta\theta} + \lambda I]^{-1} J'_{\theta} \right\}_{\underline{\theta}=\underline{\theta}_i} \quad (18)$$

$$\text{with } \begin{cases} J'_{\theta} = -2 \sum_{k=1}^K \varepsilon_k \underline{\sigma}_{k, \theta_i} & : \text{gradient} \\ J''_{\theta\theta} \approx 2 \sum_{k=1}^K \underline{\sigma}_{k, \theta_i} \underline{\sigma}_{k, \theta_i}^T & : \text{hessian} \\ \lambda : \text{monitoring parameter} \\ \underline{\sigma}_{k, \theta_i} = \frac{\partial \hat{y}_k}{\partial \underline{\theta}_i} & : \text{output sensitivity function} \end{cases} \quad (19)$$

This algorithm, known as Levenberg-Marquardt algorithm [9], insures robust convergence, even with a bad initialisation of $\hat{\underline{\theta}}$.

Fundamentally, this technique is based on the calculation of gradient and hessian, which depend on the numerical integration of the sensitivity functions $\underline{\sigma}_{k, \theta_i}$, which are equivalent to the regressor in the linear case [10].

So the Output Error method [11] is interesting because:

- no hypothesis is done about the linearity of the model.
- no data filtering procedure is necessary since the derivatives of the vector z are not calculated.
- the parameter estimation is not biased in open loop.
- the estimation is slightly disturbed by modeling error.

On the other hand, it presents some drawbacks:

- the computation volume is important because of the sensitivity functions calculations.
- the algorithm needs an initialization set point of the parameter vector $\hat{\underline{\theta}}$.
- since the method is iterative, the convergence time is longer than for the LS method, except when the initial parameter vector is very close to the optimum.
- and there may be secondary optima.

IV. COMPARISON OF THE TWO IDENTIFICATION METHODS IN SIMULATION

In practice, the self-controlled PMSM is fed by a three-phase Voltage Source Inverter (VSI). The voltages applied to the motor are created using the Space Vector Modulation technique, which controls the on and off cycles of the power inverter switches to vary the magnitude of motor voltages.

Concerning the identification protocol, as the experimental bench has no voltages sensors, voltages references will substitute for voltages measures. So as to evaluate in simulation the impact of replacing measured voltages V_d , V_q by their references on the parameter estimation results given by the two identification methods, the voltage inverter will be first neglected and modelled by a simple gain, G . Then the parameter estimation results will be compared with those obtained by introducing the Space Vector Modulation strategy in the simulation.

In a second time, so as to study the parameter estimation accuracy in stochastic case, a zero-mean independent noise will be added to the outputs of the system, which are respectively the d and q currents.

Square voltages waveforms have been chosen and applied as voltages references because it allows a good excitation of all the electrical parameters of the PMSM. Thus vector \hat{i}_d and \hat{i}_q are derived from the measured current vector i_d and i_q and are filtered as described in section III. A. 2.

A. Study in deterministic case

First of all, the voltage source inverter is neglected and modelled by a simple gain G . The identification results obtained with the Output Error method then with LS and inverse model method are given respectively in Table I.

In the deterministic case, the parameter estimation results obtained with the Marquardt algorithm or LS and inverse model method are very close to each other and converge to the exact values.

TABLE I
PARAMETERS ESTIMATION RESULTS IN THE DETERMINISTIC CASE

Parameters	Exact values	Marquardt	Least-Squares/ inverse model
R_s (Ω)	0.65	0.651	0.649
L_d (H)	$2.55 \cdot 10^{-4}$	$2.49 \cdot 10^{-4}$	$2.55 \cdot 10^{-4}$
L_q (H)	$2.55 \cdot 10^{-4}$	$2.49 \cdot 10^{-4}$	$2.55 \cdot 10^{-4}$
ϕ_f (Wb)	0.027	0.027	0.027

Fig. 2 compares the estimated currents \hat{i}_d and \hat{i}_q obtained with the Marquardt algorithm with the real ones and gives the estimation error for each current component.

Fig. 3 shows the square waveform of the voltages V_d and V_q references chosen as the identification trajectory and compares the estimated voltages V_d and V_q obtained with the L.S method and inverse model with their references.

The voltage source inverter is not neglected anymore and the control of the inverter by the Space Vector Modulation technique is introduced in the simulation of the system.

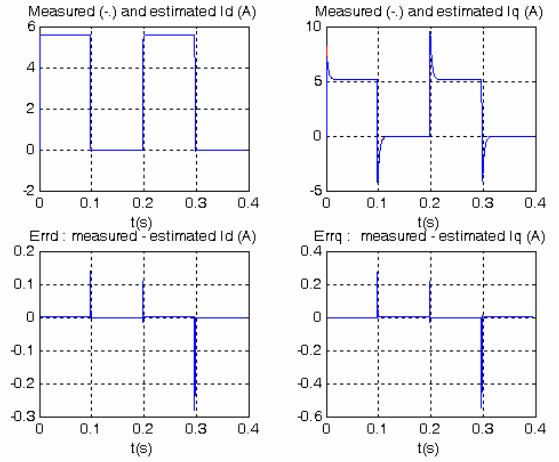


Fig. 2. Measured and estimated currents i_d and i_q with Marquardt algorithm and current estimation errors.

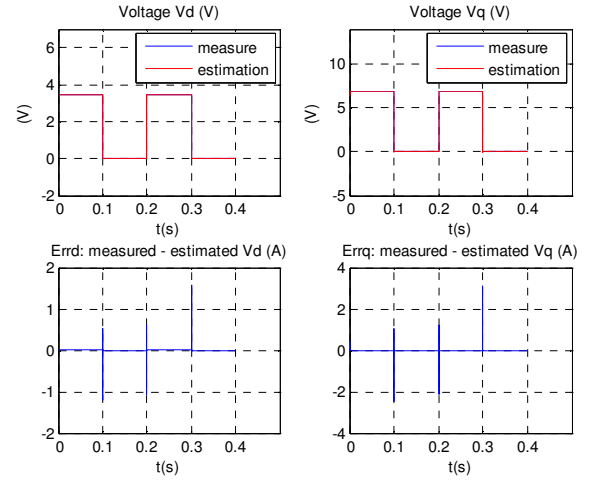


Fig. 3. Reference and estimated voltages V_d , V_q with LS method and voltage estimation errors.

Table II sums up the estimation results. It can be seen that a bias is introduced on the parameter estimations for the Marquardt algorithm as well as for the L.S method, since a modelling error appears because of the use for the identification, of the reference voltages instead of the real voltages applied to the stator windings of the PMSM. However the estimation bias is higher for the inductances L_d and L_q than for the other parameters and the bias is slightly more important for the L.S method than for the Marquardt algorithm.

Fig. 4 and Fig. 5 present the same characteristics as Fig. 2 and 3. They show that the modelling error appears in the currents and voltages estimation errors.

TABLE II
PARAMETERS ESTIMATION RESULTS AFTER VSI INTRODUCTION

Parameters	Exact values	Marquardt	Least-Squares/ inverse model
R_s (Ω)	0.65	0.6436	0.6394
L_d (H)	$2.55 \cdot 10^{-4}$	$2.33 \cdot 10^{-4}$	$2.14 \cdot 10^{-4}$
L_q (H)	$2.55 \cdot 10^{-4}$	$2.38 \cdot 10^{-4}$	$2.30 \cdot 10^{-4}$
ϕ_f (Wb)	0.027	0.0269	0.0271

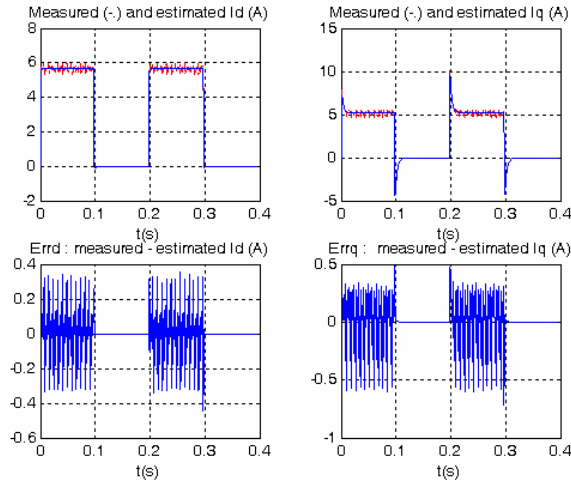


Fig. 4. Measured and estimated currents i_d and i_q with Marquardt algorithm and current estimation errors.

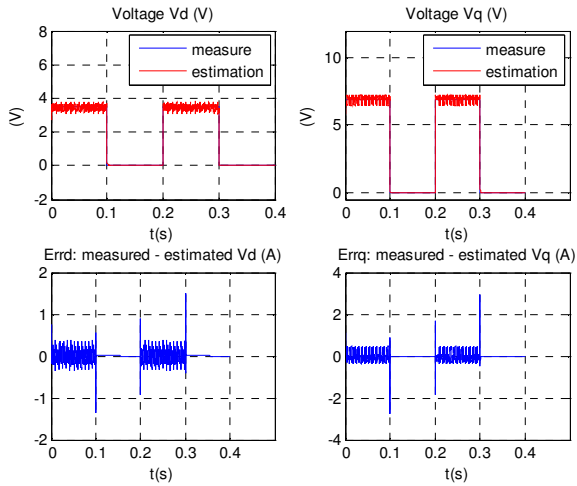


Fig. 5. Reference and estimated voltages V_d , V_q with LS method and voltage estimation errors.

B. Study in stochastic case

The voltage source inverter controlled by the Space Vector Modulation technique is not neglected anymore and a zero-mean independent measurement noise is added to the currents measures. All the parameter estimation results are then given with a confidence interval equal to $\pm 3 \sigma_{\hat{\theta}_i}$.

The Signal/Noise ratio has been chosen equal to 100. The identification results obtained with the Marquardt algorithm and with the LS and inverse model method are given in Table III.

TABLE III
PARAMETERS ESTIMATION RESULTS AFTER THE INTRODUCTION OF THE VSI
AND IN THE STOCHASTIC CASE

Parameter	Exact values	Marquardt	$\pm 3 \sigma_{\hat{\theta}_i}$	Least-Squares	$\pm 3 \sigma_{\hat{\theta}_i}$
$R_s (\Omega)$	0.65	0.644	$\pm 1.76e-3$	0.636	$3.69e-3$
$L_d (H)$	2.55e-4	2.43e-4	$\pm 1.80e-5$	1.14e-4	$1.81e-5$
$L_q (H)$	2.55e-4	2.43e-3	$\pm 0.93e-5$	1.937e-4	$1.15e-5$
$\phi_r (Wb)$	0.027	0.0268	$\pm 1.45e-4$	0.0277	$2.45e-4$

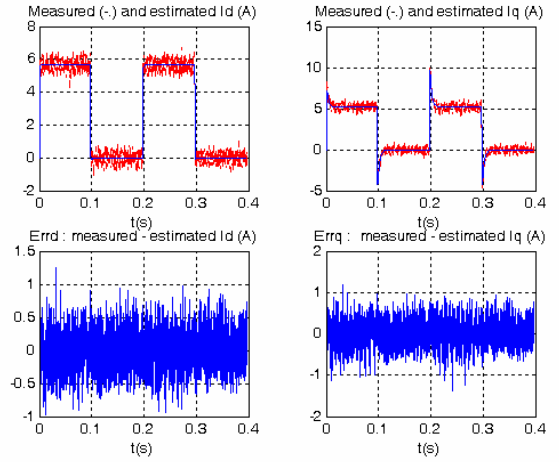


Fig. 6. Measured and estimated currents i_d and i_q with Marquardt algorithm and current estimation errors for $S/N = 100$.

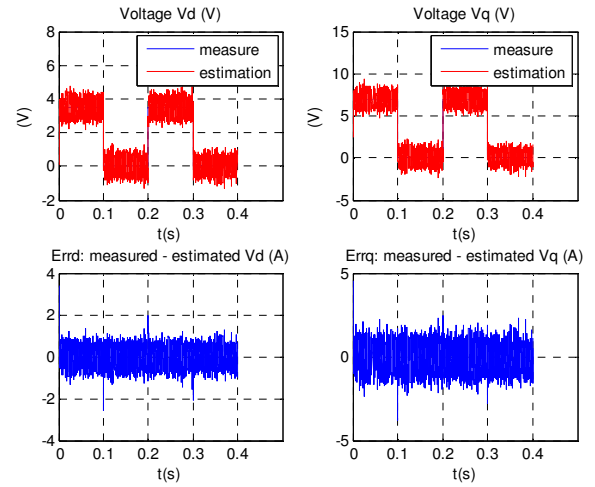


Fig. 7. Reference and estimated voltages V_d , V_q with LS method and voltage estimation errors for $S/N=100$.

Table III shows that the estimation results obtained with the Marquardt algorithm are less biased by the measurement noise than those obtained with the L.S and inverse model method, especially for the estimation of L_d and L_q .

Fig.6 compares the estimated currents \hat{i}_d and \hat{i}_q obtained with the Marquardt algorithm with the real ones, whereas Fig.7 compares the estimated voltages V_d and V_q obtained with the L.S and inverse model method with their references. The current and voltage estimation errors contain not only error modelling but also the zero-mean independent measurement noise.

V. COMPARISON OF THE TWO IDENTIFICATION METHODS IN EXPERIMENTAL CASE

The PMSM is connected to an incremental encoder to sense rotor position. A TMS320LF2407 Digital Signal Processor (DSP) allows the self-control of the motor. Two shunt resistances sense stator currents. The real direct and quadrature currents are obtained by measuring two phase currents (the 3-phase currents are considered balanced), the rotor position, and applying Park transformation.

The voltage applied to the motor is created using the Space Vector Modulation technique but only (d , q) reference voltages references are used for the identification procedure.

The identification of the electrical parameters of the PMSM is obtained experimentally after the acquisition of the currents on d and q axis and of the filtered rotor speed with a sampling period of $60 \mu s$. The derivatives of the currents are calculated by centered finite difference of the measured currents. The measures are filtered by a lowpass filter with a cut-off frequency ten times higher than the dynamics of the system.

Table IV presents the optimum of the parameter vector obtained with the Marquardt algorithm and LS method. The estimated values are compared with the values given by the constructor of the PMSM.

TABLE IV
PARAMETER ESTIMATION RESULTS IN THE EXPERIMENTAL CASE

Parameter	Constructor values	Marquardt	$\pm 3 \sigma_{\hat{\theta}_i}$	Least-Squares	$\pm 3 \sigma_{\hat{\theta}_i}$
R_s (Ω)	0.65	0.835	$2.70e-3$	0.8258	$5.51e-3$
L_d (H)	$2.55e-4$	$3.73e-4$	$1.71e-5$	$2.84e-4$	$1.94e-5$
L_q (H)	$2.55e-4$	$3.14e-4$	$1.62e-5$	$2.71e-4$	$2.11e-5$
ϕ_f (Wb)	0.027	0.0213	$4.49e-4$	0.0211	$5.77e-4$

Marquardt algorithm and LS method lead to the R_s and ϕ_f estimations which are very close to their nominal values, but to rather different estimations of the inductances L_d and L_q . LS and inverse model method gives L_d and L_q estimations closer to the values given by the constructor of the PMSM.

Fig. 8 and Fig. 9, through the estimated currents and the estimated voltages, show that they fit very well to respectively the measured currents and the reference voltages. Thus these results prove the effectiveness of the two methods.

VI. CONCLUSION

This study allows the comparison of two identification methods applied to the estimation of the electrical parameters of the PMSM used as actuator for a haptic interface. These identification methods rely on the minimisation of the input error for the LS method and of the output error for the Marquardt algorithm.

The simulation study shows that the output error method (Marquardt algorithm) is less biased by modelling error or by a zero-mean independent measurement noise than the input error method based on L.S technique.

However LS and inverse model method is much simpler to program than the Marquardt algorithm and the convergence of LS is obtained only after one iteration, whereas the Marquardt algorithm convergence needs more computational time, except if the parameter initialisation is very close to the optimum values.

REFERENCES

[1] J.E. Colgate, P.E. Grafing, M.C. Stanley, G. Schenkel, "Implementation of stiff virtual walls in force-reflecting interfaces", in Proc. IEEE-VRAIS, pp. 202-208, 1993.

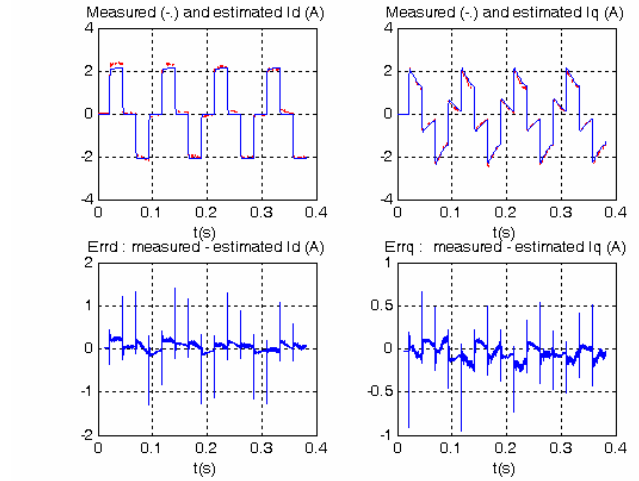


Fig. 8. Measured and estimated currents i_d and i_q with Marquardt algorithm and current estimation errors.

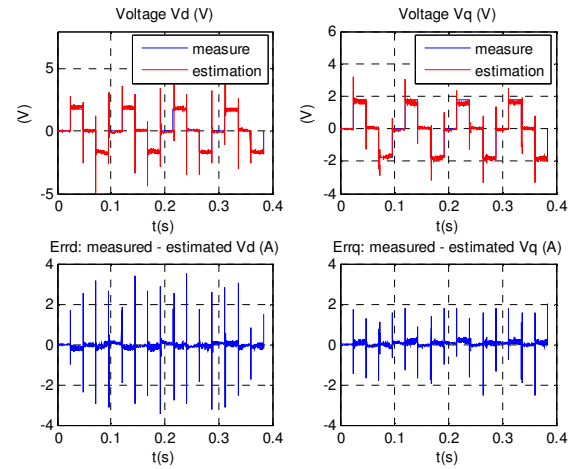


Fig. 9. Reference and estimated voltages V_d , V_q with LS method and voltage estimation errors.

[2] P.A. Millman, M. Stanley, J.E. Colgate, "Design of a high performance haptic interface to virtual environments", *IEEE Annual Virtual Reality Symposium*, pp. 216-222, 1993.

[3] F. Khatounian, S. Moreau, J.P. Louis and E. Monmasson, "Modeling and simulation of a hybrid dynamic system used in haptic interfaces". In: *8th Electrimacs Conference*, Hammamet, Tunisia, Proc., CD-ROM, ISBN 2-921145-51-0, 2005

[4] P. Vas, *Vector control of AC machines*. Ed. Clarend Press Oxford, 1990.

[5] M. Gautier, W. Khalil, "On the identification of the inertial parameters of robots". In: *27th CDC*, pp. 2264-2269, 1988.

[6] M. Gautier, P.P. Restrepo, W. Khalil, "Identification of an industrial robot using filtered dynamic model", *Proceedings, 3rd ECC*, Rome, pp. 2380-2385, 1995.

[7] M. Gautier, "Dynamic identification of robots with power model" *ICRA '97*, Albuquerque, 1997.

[8] W. Khalil, E. Dombre, *Modeling, identification and control of robots*, chapter 12. Hermes Penton, London-Paris, 2002.

[9] D. W. Marquardt, "An algorithm for Least-Squares estimation of Non-Linear Parameters", *J. Soc. Industr. Appl. Math.*, 11(2), pp. 431-441, 1963.

[10] S. Moreau, Contribution à la modélisation et à l'estimation paramétrique des machines à courant alternatif: application au diagnostic, PhD thesis, Université de Poitiers, 1999.

[11] J. Richalet, A. Rault, R. Poulliquen, *Identification des processus par la méthode du modèle*, Gordon and Breach, 1971.