Self Calibrating Procedure for a 3D Force Observer

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Self Calibrating Procedure for a 3D Force Observer

J. Gámez García‡, A. Robertsson† J. Gómez Ortega‡ and R. Johansson†

Abstract— **In robotic operations where a manipulator is involved, it is well-known that the quantities measured by a wrist force/torque sensor are corrupted by the dynamics of the end effector and manipulator. To solve this problem, an observer, which fuses information from force sensors and accelerometers, was designed recently in order to estimate the contact force exerted by a manipulator to its environment [1].**

This paper introduced a high-speed, high-accuracy, versatile, simple, and fully autonomous technique for the calibration of this robotic manipulator 3D force observer by means of active motion. To verify the improvement, an impedance control scheme was used. A dynamic model of the robot-grinding tool using the new sensors was obtained by system identification. The experiments were carried out on an ABB industrial robot with open control system architecture.

Index Terms— **Force Control, Self-calibrating Robots, Robot Control, Sensor Fusion, Observers.**

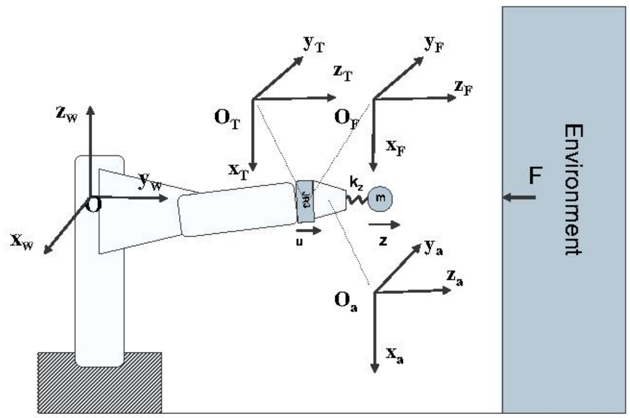

Fig. 1. Interaction between the robot tool and its environment.

I. Introduction

With the industrial development, robotic applications have been extended to flexible manufacturing systems where robots are working on either often changed or in poorly structured environments. The control in such harsh conditions become a challenging problem. In order to adapt to disturbances and unpredictable changes in the environment, robots demand rich and reliable information from a wide variety of sensors. Unfortunately, no single sensor can guarantee to deliver (acceptably) accurate information all of the time [2].

Normally, the force sensor used in robotic manipulator systems is a wrist force sensor installed between the end-effector and the last joint of the manipulator. The signals detected by the wrist force sensors are not quite accurate since the quantities measured by them are corrupted by the dynamics of the end effector and manipulator. If the manipulator starts in contact and stays in contact throughout the task, it may be reasonable to assume that the contact force can be measured directly by the force sensor, because in such case the inertial forces are far smaller than the contact force. In free motion, however, the force sensor signals consist only of the inertial forces of the end-effector and payload. Inertial force interference may be significant enough to degrade feedback signal quality and performance of the position controller if the manipulator travels at high speed or it carries a heavy tool or payload.

In order to overcome this problem, a new fusion of force and acceleration sensors was proposed in [1], which combines force sensors and accelerometers using an observer based on a Kalman Filter in order to obtain a suitable environmental force estimator in one D.O.F. In [3], this force contact observer was extended to the three Cartesian axes and also to the linear model of the robot manipulator.

On the other hand, for industrial manufacturing, sensor fusion can be interesting only if there exist fast and non-expensive calibration procedures which allow a whole integration of the sensors into the robotic system. In this sense, there has been a large amount of work reported in the literature of self-calibrating algorithms. The reader is referred to [4] and [5] for a review.

In this paper, we develop, using the force observer proposed in [3], an automatic calibration procedure for a robotic manipulator 3D force observer. The differences this method offers with respect to [6] are that the new method is extended to the linear model of the manipulator and that it is extended to the three Cartesian axis. Besides, the procedure is generalized to any number of accelerometer placed on the robot tip since several accelerometer could be used to output a better acceleration estimate using redundant sensor fusion. The main advantages this procedure offers are: its independence of the type of accelerometer, an inexpensive calibration due to the non-existent cost for extra calibration devices, and a fast execution for the simplicity of the algorithm developed.

The rest of the paper is organized as follows. Firstly, the problem formulation is presented in Sec. II. In Sec. III, we describe the new automatic calibration procedure approach. The setup of the system is described in Sec. IV. In Sec. V, the Modeling and Control is described. Section VI shows some results obtained with an industrial platform. Finally,

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the discussions and conclusions are presented in Section VII and VIII respectively.

II. Problem Formulation

A. Force Interaction

Suppose a manipulator robot as in Fig. 1. Assume that the robot dynamic for each axis i $(i = x, y, z)$ can be modelled by the following space state system

$$\begin{cases} \dot{\xi}_i = A_{R_i}\xi_i + B_{R_i}p_{ref_i} \\ y_i = C_{R_i}\xi_i \end{cases} \tag{1}$$

where $\xi_i = (\xi_{1_i}, \xi_{2_i}, \xi_{3_i})^T = (pos_i, vel_i, acc_i)^T$ and p_{ref_i} and y_i represent the position reference and the measured position for axis i. Matrices A_i, B_i and C_i have the following structure:

$$A_{R_i} = \begin{pmatrix} a_{11_i} & a_{12_i} & a_{13_i} \\ a_{21_i} & a_{22_i} & a_{23_i} \\ a_{31_i} & a_{32_i} & a_{33_i} \end{pmatrix}, B_{R_i} = \begin{pmatrix} b_{1_i} \\ b_{2_i} \\ b_{3_i} \end{pmatrix} \tag{2}$$

$$C_{R_i} = \begin{pmatrix} c_{11_i} & c_{12_i} & c_{13_i} \end{pmatrix} \tag{3}$$

This model represents the dynamic of the manipulator for each axis (i) without considering the force interaction—that is, inertial and contact forces—on its tip. On the other hand, when the manipulator moves on free or constrained space, the wrist force sensor measures two kinds of forces: the environmental or contact forces (F_i) and the inertial forces produced by accelerations $(m\ddot{\xi}_{1_i})$, that is:

$$m\ddot{\xi}_{1_i} = u_i - F_i \tag{4}$$

being m the tool mass.

Then, considering Eqs. (1) and (4), the whole dynamics of the manipulator can be represented by

$$\begin{cases} \dot{\xi}_i = A_{R_i}\xi_i + B_{R_i}p_{ref_i} + B_u u_i + B_F F_i \\ y_i = C_{R_i}\xi_i \end{cases} \tag{5}$$

where

$$B_u = \begin{pmatrix} 0 \\ 1 \\ \frac{}{m} \\ 0 \end{pmatrix}, B_F = \begin{pmatrix} 0 \\ -1 \\ \frac{}{m} \\ 0 \end{pmatrix} \tag{6}$$

Since the task undertaken requires the control of the environmental force (F_i), an observer, which fuses information from a force sensor with acceleration information and that takes into account the manipulator dynamics, was proposed in [3] to estimate this environmental force. In this paper we also propose to estimate the acceleration information using redundant sensor fusion from n_a accelerometers.

B. Description of coordinate frames and motion

As shown in Fig. 1, $O_F X_F Y_F Z_F$ and $O_{A_j} X_{A_j} Y_{A_j} Z_{A_j}$ correspond to the force sensor coordinate frame and the j-accelerometer frame respectively. The world frame is represented by $O_W X_W Y_W Z_W$ and coincides with the robot frame. $O_T X_T Y_T Z_T$ is the tool frame and coincides with the force sensor frame.

Let R_F^W denote the rotation matrix that relates the force sensor frame to the world frame and R_A^F the rotation transformation that links the accelerometer frame to the force sensor frame. Assume that the force sensor is rigidly attached to the robot tip, that the j-accelerometer is placed on the tool and that

$$R_{A_j}^F = I_{3x3} \tag{7}$$

C. Elements to be Computed

Instead of seeking the exact values in terms of any a priori system knowledge, we let the algorithm itself to estimate them [5]. Thus, we are treating the system as being completely "black" to us. Our basic idea for self-calibration is to use designed motion sequences, e.g., pure translational motions, to estimate the following parameters used by the contact force observer.

Determination of the tool mass: To determine the mass of the tool, the procedure orients the robot in order to use the gravity acceleration as input.

Accelerometer calibration: For the industry, the main constraint of a desired calibration procedures is that it should require no extra hardware and should be carried out automatically. In the accelerometer case, although accelerometers calibration parameters are known from the manufacturer, but as a signal-conditioning stage normally has to be used to measure the sensors output, the new calibration parameters need to be estimated.

To estimate the accelerometers parameters, the force sensor together with a set of motions in free space are used. Consider a number of n_a accelerometers placed on the robot tool. Basically, the equation that relates for each accelerometer j $(j = 1, 2..n_a)$ its electrical signal and the true acceleration (measured in ms^{-2}) is

$$\begin{aligned} V_j &= K_{g_j} a_j + V_{o_j} = \\ &= \begin{pmatrix} K_{g_{x,j}} & 0 & 0 \\ 0 & K_{g_{y,j}} & 0 \\ 0 & 0 & K_{g_{z,j}} \end{pmatrix} \begin{pmatrix} a_{x,j} & a_{y,j} & a_{z,j} \end{pmatrix} + \begin{pmatrix} V_{o_{x,j}} \\ V_{o_{y,j}} \\ V_{o_{z,j}} \end{pmatrix} \end{aligned} \tag{8}$$

where $V_j = [V_{x,j} V_{y,j} V_{z,j}]^T$ is the sensor output voltage for accelerometer j, K_{g_j} is the sensitivity that relates the output voltage with the acceleration a_j (ms^{-2}) and V_{o_j} is the zero offset.

To fuse redundant information from different accelerometers and output a better acceleration estimation, it is necessary to handle this redundancy by using the error covariance of each sensor obtaining an optimal global estimate that combines a maximum of information [7]. The error covariance is defined as $P_j = [P_{x,j} P_{y,j} P_{z,j}]^T$ which represents the covariance between the i-axis acceleration measured by the j-accelerometer and the force sensor measurement of its respective axis scaled inversely to the tool mass. Note that the force sensor measurements, in this case corresponding to the inertial forces, are assumed to be calibrated. Finally, the acceleration estimate $\hat{a}_i$ for each axis i is obtained applying the following equation [8]

$$\hat{a}_i = \frac{\sum_{j=1}^{n} \frac{a_{i_j}}{P_{i_j}}}{\sum_{j=1}^{n} \frac{1}{P_{i_j}}} \tag{9}$$

Note that the smaller the error covariance of an estimate, the larger its contribution to the global estimate.

Linear model of the manipulator: For each axis i, a linear model showing the relation between the position reference p_{ref_i} and the current position of the robot tip ξ_i, has to be calculated. The model proposed was an output-error model

$$\mathscr{M}: \qquad y_k = \frac{B(q)}{F(q)} u_{k-d} + e_k \tag{10}$$

where k is sample index, q is the forward shift operator ($h = 4$ ms), $\{e_k\}$ normally distributed white noise. $nb = nf = 3$ and the delay d is 1.

In order to determine the manipulator linear model referenced in Eq. (1), we convert Eq. (10) to the state space form obtaining the corresponding matrices. To estimate the output-error model, the System Identification ToolBox of Matlab was used [11].

Design of the observer gains: In an industrial process, it is common to get signals corrupted by additive noise or interference. In some cases, the noise filtering procedure has the disadvantage of requiring excessively elaborate and costly hardware, because some signals and their respective noise might share a similar frequency spectrum or the frequency bands of the signal of interest and the noise are very close. [9].

With simple addition of accelerometer sensors we would have a final signal with too much noise. The solution presented with the force observer reduced this problem but the selection of the observer gains requires a trade off between the noise and a fast response of our observer.

From [3], the contact force observer ($\widehat{F_{X_F}}$) with low pass properties has the following structure

$$\begin{aligned} \widehat{F}_i \;&=\; \frac{m}{a_{12_i}}((a_{12_i}\Lambda_{2_i} + a_{13_i}\Lambda_{3_i})\widetilde{\xi}_{1_i} - (a_{12_i}k_{24_i} \\ &+\; a_{13_i}k_{34_i})\ddot{\xi}_{1_i} + (a_{12_i}\frac{k_{24_i}}{m} + a_{13_i}\frac{k_{34_i}}{m})u_i) \end{aligned} \tag{11}$$

where $k_{(..)_i}$ are the observer gains for i-axis, u_i is the force sensor measurement, m is the tool mass and ξ_{1_i} is the position for axis i. Λ_{2_i} and Λ_{3_i} are parameters to be estimated [3]. The observer dynamics are summarized as the state space system:

$$\begin{cases} \dot{\widetilde{\xi}}_i &= (A_i - K_iC_i)\widetilde{\xi}_i + K_iC_i\xi_i + B_F F_i + k_{1_i} D_{p_i} \\ & +k_{2_i} D_{u_i} u_i - K_i y_i \\ \widetilde{F}_i &= F_i - \dfrac{m}{a_{12_i}}(\beta_i - (a_{12_i}\Lambda_{2_i} + a_{13_i}\Lambda_{3_i})\widetilde{\xi}_{1_i}) \end{cases} \tag{12}$$

where K_i are the observer gains for axis i.

III. 3D Force Observer Automatic Procedure

For this work, a static calibration is proposed to determine the offset (V_{o_j}) and a dynamic calibration to calculate its sensitivity (K_{g_j}), all of them for each accelerometer j. Later, Eq. (9) is applied to integrate the information from the different accelerometers. Regarding the observer, note that the gain (K_i) is extremely important and determines the performance of the force estimator. To achieve good force estimations the environmental force should be big enough to deflect over the noise level of the system. The Kalman Filter solution will be used for the automatic procedure. Considering that stochastic disturbances are present in our system and supposing that the process noise v_{ξ_i} and the inputs noise v_{y_i} for axis i are white, Gaussian, zero mean, and independent with constant covariance matrices Q_i and R_i respectively, then there exists an observer gain (K_i) for the state space system (12) that minimizes the estimation error variance due to the system noises [3]. Then, these gains are calculated as

$$K_i = P_i C_i^T R_i^{-1} \tag{13}$$

where the constant matrix P_i is computed as the solution of the Riccati matrix equation

$$P_i A_i^T + A_i P_i - P C_i^T R^{-1} C_i P_i + Q_i = 0 \tag{14}$$

The observer gains are chosen to minimize the estimation error variance due to the system noises, but not the variance due to the environmental forces. Note that gain k_{34_i} is constrained to

$$k_{34_i} = \frac{1 - a_{12_i}^2 k_{24_i}}{a_{13_i} a_{12_i}} \tag{15}$$

in order to fulfill the constraint imposed by Newton's law in Eq. (11) [3].

A. Automatic Procedure

In this section we present an automatic procedure to solve the fusion of accelerometers and force sensors attached to the manipulator robot. This algorithm aims to manage any kind of accelerometer—e.g., a capacitive one—and any number of them to integrate their data with the force sensor data in order to obtain a contact force observer with a suitable properties in terms of response and filtering. The complete procedure is shown as follows. Note that $t_0 < t_1 < t_2 < t_{3_x} < t_{4_x} < t_{3_y} < t_{4_y} < t_{3_z} < t_{4_z}$.

1) The robot is placed with the tool so that $R_T^W = R_{T_1}^W$ being

$$R_{T_1}^W = Rot(Y_W, \alpha) Rot(Z_W, \delta) Rot(X_W, \theta) \tag{16}$$

which yields

$$R_{T_1}^W = \begin{pmatrix} c_\alpha c_\delta & -c_\alpha s_\delta c_\theta - s_\alpha s_\theta & c_\alpha s_\delta s_\theta - s_\alpha c_\theta \\ s_\delta & c_\delta c_\theta & -c_\delta s_\theta \\ -s_\alpha c_\delta & s_\alpha s_\delta c_\theta + c_\alpha s_\theta & -s_\alpha s_\delta s_\theta + c_\alpha c_\theta \end{pmatrix} \tag{17}$$

with $s = sin$, $c = cos$, $\alpha = \frac{\pi}{2}$ rad, $\delta = \frac{\pi}{2}$ rad and $\theta = \frac{-\pi}{2}$ rad. Initialize the force sensor and set $t_0 = t$.

2) The tool is maintained in that position from time t_0 to time t_1 avoiding any movement. Calculate

$$u^h_{Z_F} = \frac{1}{(n_{t_1} - n_{t_0})} \sum_{k=n_{t_0}}^{n_{t_1}} u_{Z_F}(k) \tag{18}$$

where n is the number of samples per second, $n_{t_0} = t_0 n$, $n_{t_1} = t_1 n$ and $u_{Z_F}(k)$ is the z-axis JR3 measurement for sample k and

$$V_{o_{i,j}} = \frac{1}{(n_{t_1} - n_{t_0})} \sum_{k=n_{t_0}}^{n_{t_1}} V_{i,j}(k) \tag{19}$$

where $V_{o_{i,j}}$ is the offset of accelerometer j for axis i, $V_{i,j}$ is the j-accelerometer output voltage for axis i where i is equal to y and z for this step.

3) The robot is placed with the tool so that $R^W_T = R^W_{T_3}$ (R^W_T for step 3) being

$$R^W_{T_3} = Rot(Z_W, \delta) Rot(X_W, \theta) \tag{20}$$

which yields

$$R^W_{T_3} = \begin{pmatrix} c_\delta & -s_\delta c_\theta & s_\delta s_\theta \\ s_\delta & c_\delta c_\theta & -c_\delta s_\theta \\ 0 & s_\theta & c_\theta \end{pmatrix} \tag{21}$$

Set $t_2 = t$.

4) The tool is maintained in this position from time t_2 to time t_3 avoiding any movement. Then calculate

$$u^v_{Z_F} = \frac{1}{(n_{t_3} - n_{t_2})} \sum_{k=n_{t_2}}^{n_{t_3}} u_{Z_F}(k) \tag{22}$$

$$V_{o_{x,j}} = \frac{1}{(n_{t_3} - n_{t_2})} \sum_{k=n_{t_0}}^{n_{t_1}} V_{x,j}(k) \tag{23}$$

where $n_{t_2} = t_2 n$ and $n_{t_3} = t_3 n$.

5) Calculate the mass (m) as

$$m = \frac{\mid u^v_{Z_F} - u^h_{Z_F} \mid}{g} \tag{24}$$

where g is the gravity acceleration.

6) For each axis i

- A step change in i is applied to the robot from t_{3_i} to t_{4_i}. Calculate $K_{g_{i,j}}$ as

$$K_{g_j} = ((\theta_{i,j}(k)^T \theta_{i,j}(k))^{-1} \theta_{i,j}(k)^T Y_i(k))^{-1} \tag{25}$$

where $\theta_{i,j}$ and Y_i are vectors of dimension $(t_{4_i} - t_{3_i})n$ with n the number of samples per second and

$$\begin{aligned} \theta_{i,j}(k) &= V_{i,j}(k) - V_{o_{i,j}} \\ Y_i(k) &= \frac{u_i(k)}{m} \end{aligned}$$

with $(k = t_{3_i} n .. t_{4_i} n)$.

- The following output-error model is identified (Eq. 10)

$$\mathscr{M}: \quad \xi_i = \frac{B(q)}{F(q)} p_{ref_{i_{k-d}}} + e_k \tag{26}$$

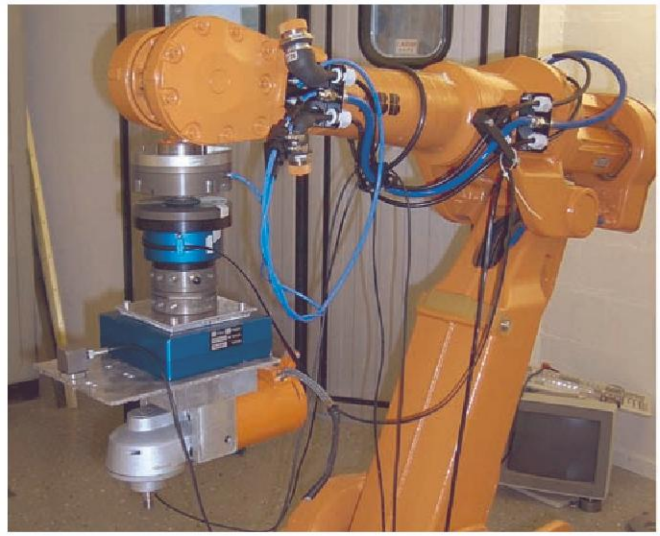

Fig. 2. The experimental setup. An ABB industrial robot IRB 2400 with an open control architecture system is used. The impedance control is performed perpendicular to the screen. Whereas the accelerometer is placed on the grinding tool, the Optidrive is placed between the tool and the JR3 sensor.

where ξ_i represents the axis position and p_{ref_i} is the reference position for axis i. $nb = nf = 3$ and $d = 1$.

- Convert the former model into state space equation as in Eq. (1).
- The covariance matrices Q_i and R_i are calculated.
- The observer gains are calculated using Eqs. (13) and (14).
- Following constraint imposed by equation (15), set

$$k_{34_i} = \frac{1 - a^2_{12_i} k_{24_i}}{a_{13_i} a_{12_i}} \tag{27}$$

Note that this new value does not affect the stability of the observer, only its static gain [3].

7) The final acceleration estimate is obtained as

$$\hat{a}_i = \frac{\sum_{j=1}^{n} \frac{K^{-1}_{g_j}(V_j - V_{o_j})}{P_j}}{\sum_{j=1}^{n} \frac{1}{P_j}} \tag{28}$$

B. Speed Performance

Analyzing the algorithm for the automatic procedure, it is well appreciated that most time is consumed by the robot movements. Therefore, depending on the time the manipulator needs to carry out the movements and wait to stabilize in the goal positions, the execution of the procedure will last.

For the whole procedure applied to our ABB robot, the algorithm requires about 40s to calibrate the contact force observer. Once the movements are carried out, the number of arithmetic operations (N) calculated are approximately

$$N = ((t_1 - t_0) + 2(t_3 - t_2) + 3(t_4 - t_3))n \tag{29}$$

where n is the number of samples per second.

IV. Experimental Set-up and Methods

The robot-tool system is composed of the following devices and sensors (Fig. 2): an ABB robot; a wrist force sensor; a compliant grinding tool—*i.e.*, a device called Optidrive® that links the robot tip and the tool offering a compliant response for the x axis of the robot—and, finally, an accelerometer.

The robotic system used in this experiment was based on an ABB robot (Irb 2400) situated in the Robotics Lab at the Department of Automatic Control, Lund University. A totally open architecture is its main characteristic, permitting the implementation and evaluation of advanced control strategies. The controller was implemented in Matlab/Simulink using the Real Time Workshop of Matlab, and later compiled and linked to the Open Robot Control System [10]. The wrist sensor used was a DSP-based force/torque sensor of six degrees of freedom from JR3. The tool used for our experiments was a grinding tool with a weight of 13 kg. The accelerometer was placed on the tip of the tool to measure its acceleration. The accelerometer and Optidrive signals were read by the robot controller in real time via an analog input. The accelerometer used for our experiment was a capacitive one with a frequency range of 0-500 Hz:

V. Modeling and Control

For the environment, a vertical screen made of cardboard was used to represent the physical constraint. To verify the observer performance and in consequence, the proposed automatic calibration procedure, *impedance control* was used [12]. Regarding the experiments carried out to verify the automatic procedure, they consisted of three phases: an initial movement in free space, a contact transition, and later, a movement in constrained space.

The model used to design the impedance controllerwas considered using the three Cartesian direction of the robot. A linear dynamic model showing the relation between the position reference (p_{ref_i}) and the current position of the robot tip (ξ_i) was identified. An output-error model was calculated using the System Identification Toolbox of Matlab ('oe' function), the resulting model being as follows:

$$\begin{cases} \dot{X}_i = A_{d_i} X_i + B_{d_i} x_{p_{ref_i}} \\ y_i = C_{d_i} X_i \end{cases} \qquad (30)$$

where $X_i = [\xi_i, \dot{\xi}_i, \ddot{\xi}_i]^T$ for $i = x, y,$ and z. The impedance control approach was chosen as the control law to verify the properties of the new force observer. In this sense, a LQR controller was used to make the impedance impedance relation variable go to zero [12] for the three axes (x, y, z). The control law applied was

$$u_i = -LX_i + c_i \widehat{F}_i + l_r p_{ref_i} \qquad (31)$$

with c_i as the force gain in the impedance control, $\widehat{F}_i$ the estimated environmental force, which in our case it was estimated using the force observer, p_{ref_i} the position reference for axes (x, y, z) and l_r the position gain constant, L being calculated considering Eq. (30).

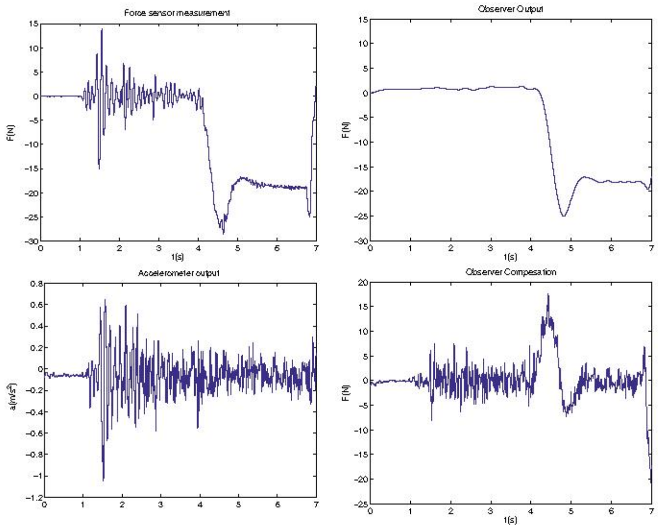

Fig. 3. Force measurement from the wrist sensor JR3 (upper-left), force observer output (upper-right), acceleration of the robot tip (lower-left) and observer compensation (lower-right). These results were obtained for x-axis.

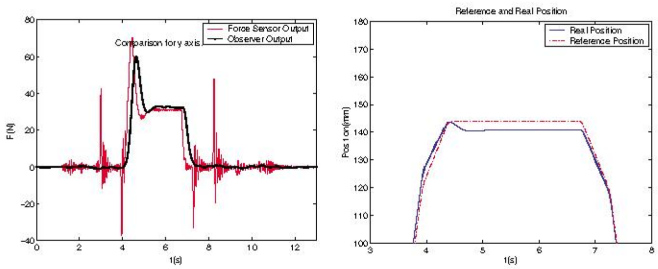

Fig. 4. Comparison between the observer output and the force sensor measurement for axis y (left). Real and reference position for y axis (right).

VI. Results

The experiments carried out on the real robot to verify the performance of the observer consisted of three phases for all axes (x, y, z): an initial movement in free space, a contact transition, and later, a movement in constrained space. The velocity during the free movement was 300mm/s and the angle of impact was 30 with respect to the $O_T Z_T$ axis.

The experiments for axis x are shown in Fig. 3, which depicts, at the top, the force measurement from the JR3 sensor (left) and the force observer output (right) while at the bottom, the acceleration of the tool getting into contact with the environment (left), and the observer compensation (right) are shown. Note that the observer eliminates the inertial effects. Fig. 4 depicts the force sensor output and the force observer output for axis y (left). Note that the observer eliminates the inertial effects and how the transition of contact phase ($t = 4s$) is improved since the observer eliminates the perturbations introduced by the inertial forces.

On the other hand, the reference and the real position of axis y of the robot during the experiment, where the force observer information was used to execute the impedance control, are shown in Fig. 4 (right). The experiment for

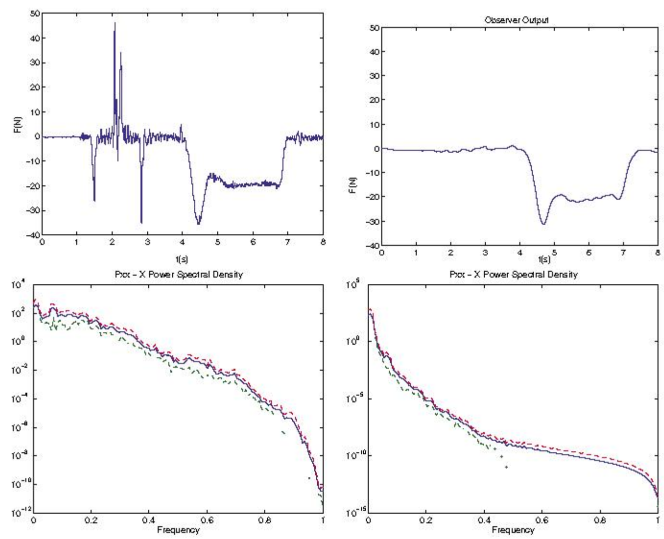

Fig. 5. Force measurement from the wrist sensor JR3 (upper-left), force observer output (upper-right), power spectrum density for the composed signal $u - m\ddot{x}$ (lower-right) and observer output power spectrum density (lower-left). These results were obtained for z-axis.

axis z is shown in Fig. 5 which depicts, at the top, the force measurement from the JR3 sensor (left) and the force observer output (right) while at the bottom, the power spectrum density for the composed signal $u - m\ddot{\xi}_z$ (left) and the observer output power spectrum density (right). Note how the observer cuts off the noise introduced by the sensors.

VII. Discussion

As mentioned before, to calibrate a force observer which fusions force, position and acceleration sensors, an automatic procedure was proposed in [6]. Its main drawback was that it considered only 1 D.O.F. For industrial processes—i.e. deburring, grinding—where robots work in poorly structured environments, it is not enough to estimate the contact force in only one D.O.F. The new algorithm improves this aspect. In addition, the new procedure also considers the linear dynamics of the robot, improving the response of the force observer. Other difference this new self-calibrating procedure offers is, based on the idea that several low-cost accelerometers could be used to output a better acceleration estimate, the procedure deals with any number of accelerometer placed on the robot tip. The new generalized procedure is open, using redundant sensor fusion, to any number of accelerometers permitting to obtain a unified and a more accurate representation of the tool acceleration.

On the other hand, note that the proposed procedure uses the force sensor measurements as references to identify part of the calibration parameters. It means that the final accuracy of the procedure is subject to the force sensor accuracy, which is calibrated from the manufacturer. A deep error analysis has to be done in order to reveal what the critical factors influencing the accuracy are, giving rise to various means for improving accuracy. This analysis was not included by lack of space.

VIII. Conclusions

This paper introduced a versatile, simple, accurate and fully autonomous technique for the calibration of a robotic manipulator 3D force observer which fuses data from force sensor and accelerometers. The new method considers the linear model of the manipulator, it is generalized to any number of accelerometers placed on the robot tip and it is also extended to the three Cartesian axes. This procedure aims at offering a *'plug-and-play'* solution for the integration of different kind of accelerometers with the final goal of obtaining an observer capable of estimating the contact force exerted by an industrial robotic manipulator.

The final observer implies the improvement of the robot behavior where force control is involved and specifically where the robot tasks lead to a contact between the robot tool and the environment. The behavior of the observer and the performance of the proposed procedure were successfully verified attaching an accelerometer to an industrial robot.

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