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Real-time identification using a classical nonlinear optimization algorithm and the flatness properties of a system : Application to an intensity/pressure converter

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Abstract

This article presents a modification of a classical nonlinear identification algorithm, which permits then on-line identification (or real-time identification). This modification is particularly based on using nonlinear optimization algorithm, not with a classical model of the process, which needs a numerical integration algorithm to solve it, but with the flatness properties of the model of the process (Fliess et al., 1995). The states of the system are then obtained without any integration, which follows a significant saving of calculation time. This modified method is applied to on-line identification of the parameters of a nonlinear model of an intensity/pressure converter (i/p converter), used to supply air pressure inside an artificial pneumatic muscle used like actuator on the robots of the laboratory. To illustrate the method, experimental results are given and discussed.

1 Introduction

The application of identification methods for nonlinear systems is much more delicate than for linear one's. Indeed, for linear systems, there exist many methods quite easy to apply. The methods based on mean squares algorithm are certainly the most common (extended mean squares, generalized mean squares, least mean squares…) (Landau, 1988). The advantage of these methods is that they do not need process simulator, but work only with experimental data. This advantage and the easiness to write these methods under an iterative form show that they are adapted to real-time applications, in particular for adaptive control algorithms (Richalet, 1991).

When the system is described by a nonlinear model, above methods are not applicable. Nonlinear parametric identification needs the use of nonlinear programming tools (Gradient, Newton, Gauss-Newton…) (Norton, 1986), and the application of these tools is not always possible. Although an iterative form of these algorithms exists, it uses all data at each iteration and needs a process simulator (the response of the system is obtained by numerical integration of differential equations describing process behaviour, using a lot of computation time).

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The computation time is generally too long to able an application to an on-line identification. In this paper, we propose some modifications to apply these nonlinear techniques in an on-line identification process. The same nonlinear identification algorithm is not applied to the classical model of the process, but to the flat differentially model ; the states vector X and inputs U of the flat differentially model of a system are obtained directly without integration (see section 3), from which computation time for identification process is largely reduced (Sanchez and Mahout, 1998-1999). The identification process does not use all available data, but the identification is performed inside a sliding window of F points (see section 4.2.2), the position of the window varies as the manipulation proceeds. The "Stop-tests" of the optimization algorithm will be less restrictive than those used in an off-line identification because in this case, the question of computation time is crucial. This modified method is applied to on-line identification of the parameters of a model of an i/p converter.

The article is organized as follow:

Firstly, the studied system will be briefly described, and a knowledge model will be designed. Then we note that this model has flatness properties, which permit to design its flat differentially model. The modified identification method will be developed and applied. Different experimental results will be given and discussed. Finally, we conclude about the method, and the future works, in particular the use of this method in an adaptive control algorithm will be wording.

2 Description and modelling of the studied system

The studied system is an i/p converter, used for supplying air pressure inside an artificial pneumatic muscle, developed in the laboratory (Tondu and Lopez, 1995). The i/p converter and the artificial pneumatic muscle form this pneumatic muscle actuator. To obtain an accurate model of the actuator, in the aim to design an efficient control law, a knowledge model of the i/p converter is used. The i/p converter is an electropneumatic converter, controlled by continuous current SAMSON 5288. The model of the process is given by :

$$\ddot{P}_s = \frac{\gamma.(1+P_s)}{\tau_{bp}.V}\left[C.G_{bp}.u - P_s.G_{bp}.(1+C.D) - (\dot{V} + \tau_{bp}\ddot{V}\right] - \frac{\dot{P}_s}{\tau_{bp}} \qquad \text{(eq. 1)}$$

with

P_s	:	Output pressure of the converter
u	:	Input (corresponding to a desired output pressure)
γ	:	Constant equal to 1.4 for air
G_{bp}, τ_{bp}, C, D	:	Parameters which must be identified

(See (Boîtier, 1996) for details of modelling)

To study the i/p converter independently of the inherent muscle properties, the converter is connected to a constant volume. In this case $V = C^{te}$, and so $\dot{V} = 0$ and $\ddot{V} = 0$.

Setting $x_1 = P_s$ and $x_2 = \dot{P}_s$, the following model is obtained :

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \dfrac{\gamma.(1+x_1)}{\tau_{bp}.V}\left[C.G_{bp}.u - G_{bp}.(1+C.D).x_1\right] - \dfrac{x_2}{\tau_{bp}} \\ y = x_1 \end{cases} \qquad \text{(eq. 2)}$$

3 Flatness, flat differentially model of a system

After a brief introduction about flatness, a definition of flat differentially model of a system will be given. Then, the flat differentially model of the studied process will be calculate.

3.1 Introduction

Fliess et al. have originally studied differentially flat systems in the context of differential algebra (Fliess et al., 1992) and later using Lie-Bächlund transformation (Fliess et al., 1993). Differentially flat systems have attracted considerable attention recently and, although there are no general methods for determining whether or not a particular system is flat, it is know that many systems of interest in application are flat (Murray et al., 1996).

3.2 Definition

A system is differentially flat if we can find a set of outputs (equal to number of inputs) such that all states and inputs of the system can be determined from these outputs without integration. More precisely, if the system has the states $x \in \Re^n$, and the inputs $u \in \Re^m$, then the system is flat if we can find output $y \in \Re^m$ (called flat output) of the form :

$y = y(x, u, \dot{u}, ..., u^{(\alpha)})$ such that $\begin{cases} x = x(y, \dot{y}, ..., y^{(\beta)}) \\ u = u(y, \dot{y}, ..., y^{(\beta)}) \end{cases}$ with α and β integers.

3.3 Application to the studied system

For the system described by (eq. 2), the flat differentially model is found immediately. Setting $y = x_1 = P_s$ like flat output, we note that the input u of the system is function of $y = x_1, \dot{y} = \dot{x}_1 = x_2, \ddot{y} = \ddot{x}_1 = \dot{x}_2$. The expression of flat differentially model of the system can be written :

$$u = \frac{V}{\gamma.G_{bp}.C.(1 + x_1)}.(\dot{y} + \tau_{bp}.\ddot{y}) + \frac{1 + C.D}{C}.y \qquad \text{(eq. 3)}$$

Remark : For more complex systems with higher order, the expression of the flat differentially model can not be immediately deduced like previously, but the use of Lie-Bächlund algebra is required. It is particularly the case for the model of the actuator (i/p converter + muscle), which is a fourth order, and the expression of the flat differentially model is complex.

4 Description of identification method

First, the general principle of nonlinear optimization method will be described, and then the modifications of the algorithm, to allow on-line identification, will be developed with its application to the i/p converter.

4.1 Principle of the method

The method is based on the minimization of a criterion function of the difference between the output of real system Os and the response of the model of the system Om (fig. 1).

This minimization is performed thanks to a nonlinear optimization algorithm, which return the optimal values of the parameters.

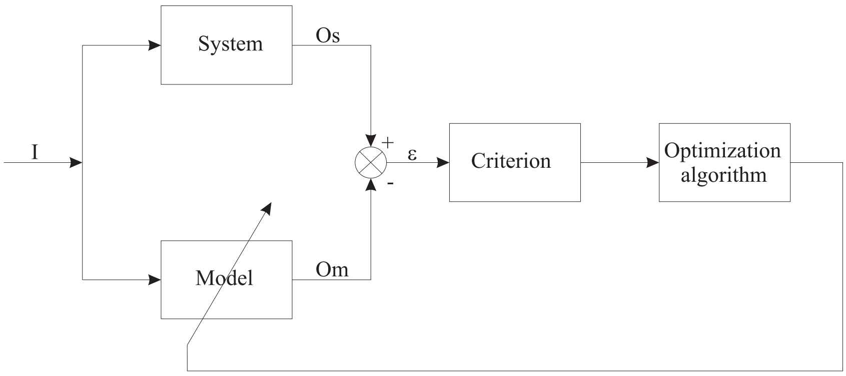

Figure 1 : Principle of identification method

Remark : For the "classical case", I = u and Om = Ps (desired pressure) ; for the "flat case", $I = (Ps, \dot{P}s, \ddot{P}s)$ and Om = u.

The chosen criterion is a quadratic criterion and the optimization algorithm chosen is a damped Gauss-Newton algorithm, used on account of convergence rapidly (Walter and Pronzato, 1997).

4.1.1 Criterion

The criterion can be write :

$$J(\Phi) = \sum_{k=B}^{k=E} \varepsilon_k^{\ 2} = \sum_{k=B}^{k=E} \left(O_{s,k} - O(\Phi)_{m,k}\right)^2 \qquad \text{(eq. 4)}$$

where

Φ	:	Parameters vector
$O_{s,k}$	:	Output of the system, at k^{th} point
$O(\Phi)_{m,k}$	:	Output of the model, at k^{th} point
B	:	Point of begin of identification process
E	:	Point of end of identification process

4.1.2 Optimization algorithm : damped Gauss-Newton algorithm

The damped Gauss-Newton algorithm is one of the most used algorithms in nonlinear programming (Walter and Pronzato, 1997). It is described by the following recurrence :

$$\Phi_{i+1} = \Phi_i + \Delta\Phi_i = \Phi_i - \mu.Ha(\Phi_i)^{-1}.Grad(\Phi_i) \qquad \text{(eq. 5)}$$

with

Φ	:	Parameters vector
$\Delta\Phi$	:	Variation parameters vector
μ	:	Step size, which is adjusted so that $J(\Phi_{i+1}) < J(\Phi_i)$
Grad (Φ_i)	:	Criterion gradient vector
Ha $(\Phi_i)^{-1}$	:	Inverse criterion hessian matrix

Remark : The Gauss-Newton method uses an approximation of the hessian matrix. This approximation does not take into account the terms of second order ; consequently the matrix is positive semi-definite, that assures to reach a minimum of the criterion. The expressions of Φ, $\mathrm{Grad}(\Phi)$ and $\mathrm{Ha}(\Phi_i)^{-1}$ are given by

$$\Phi = \begin{bmatrix} \Phi_1 \\ \ldots \\ \Phi_{Np} \end{bmatrix} \quad \mathrm{Grad}(\Phi) = \begin{bmatrix} -2\sum_{k=B}^{k=E} \varepsilon_k(\Phi).\sigma_{\Phi_1} \\ \ldots \\ -2\sum_{k=B}^{k=E} \varepsilon_k(\Phi).\sigma_{\Phi_{Np}} \end{bmatrix} \quad \mathrm{Ha}(\Phi) = \begin{bmatrix} -2\sum_{k=B}^{k=E} \sigma_{\Phi_1}{}^2 & \ldots & -2\sum_{k=B}^{k=E} \sigma_{\Phi_1}.\sigma_{\Phi_{Np}} \\ \ldots & \ldots & \ldots \\ -2\sum_{k=B}^{k=E} \sigma_{\Phi_{Np}}.\sigma_{\Phi_1} & \ldots & -2\sum_{k=B}^{k=E} \sigma_{\Phi_{Np}}{}^2 \end{bmatrix} \quad \text{(eq. 6)}$$

with Np : Number of parameters which must be identified

$\sigma_{k\Phi_i} = \dfrac{\partial O(\Phi)m,k}{\partial \Phi_i}$: Sensibility function of the output model, in relation with the parameter Φ_i.

4.2 Development of the modified algorithm

4.2.1 Use of flat differentially model of the system

Usually, the identification algorithm is applied to a classical model of a system (eq. 1-2), which needs numerical integration algorithm to solve it, using significant computation time. The use of a flat differentially model on the identification process permits to save not-negligible computational time (Sanchez and Mahout, 1998-1999). Indeed, a flat differentially model just needs first and second order output derivatives. These derivatives are obtained by using a numerical derivation recurrence (eq. 7), based on the Lagrangian interpolation polynomial form (Demidovitch and Maron, 1970).

$$\dot{y}_n = \frac{1}{12.h}\left[-25.y_n + 48.y_{n-1} - 36.y_{n-2} + 16.y_{n-3} - 3.y_{n-4}\right] \quad \text{(eq. 7)}$$

where h is the sampling time

For the flat differentially model of the i/p converter (eq. 3), the output of the "system" is the input u of the i/p converter. The physical output of the system x_1 is used to calculate u. Like u is a vector-valued function of $(x_1, \dot{x}_1, \ddot{x}_1)$, so the sensibility coefficients (noted σ), necessary to the damped Gauss-Newton method are given as :

$$\sigma_{G_{bp}} = \frac{\partial u}{\partial G_{bp}} = -\frac{V}{\gamma.C}.\frac{1}{G_{bp}{}^2}.\frac{\dot{x}_1 + \tau_{bp}.\ddot{x}_1}{1 + x_1} \quad \text{(eq. 8)}$$

$$\sigma_{\tau_{bp}} = \frac{\partial u}{\partial \tau_{bp}} = \frac{V}{\gamma.G_{bp}.C}.\frac{\ddot{x}_1}{1 + x_1} \quad \text{(eq. 9)}$$

$$\sigma_c = \frac{\partial u}{\partial C} = \frac{1}{C}.(D.x_1 - u) \quad \text{(eq. 10)}$$

$$\sigma_D = \frac{\partial u}{\partial D} = x_1 \quad \text{(eq. 11)}$$

4.2.2 "Sliding window"

Usually, the identification algorithm is used off-line because the necessary computation time does not allow an on-line (or real-time) application. To obtain real-time application of this algorithm, which means that the parameters are varying as the manipulation proceeds, the identification process is applied inside a "sliding window" of F points.

1. For (F-1) first points, the identification process is disable, but the experimental data are conserved (inputs, outputs…).
2. When F points are obtained, the identification process is enable, and the "sliding window" slide as the manipulation proceeds (points [1⇒F], [2⇒(F+1)]…[B⇒E]…[(N-F)⇒N]), with (E-B) = F and N is the total number of measurements.

4.2.3 "Stop-tests"

It is necessary to define when it becomes unnecessary to continue iterations. The stop conditions used are double :

1. A criterion test : $\tau_1 = \left|J(\Phi_k) - J(\Phi_{k-1})\right| < \delta_1$. The difference between two successive values of the criterion is smaller than a fixed limit δ_1.
2. A parameters test : $\tau_2 = \sqrt{\sum_{i=1}^{i=N_p} (\Delta\Phi_i)^2 / \sum_{i=1}^{i=N_p} (\Phi_i)^2} < \delta_2$ with N_p : Number of parameters. The value of τ_2 becomes smaller than a precision value δ_2.

Like the identification process is iterative, besides this two stop-test, it has been necessary to do that the number of loop which permits to adapt the parameters is executed at the most **kmax** times.

4.3 Diagram of the method

The figure 2 illustrates the method.

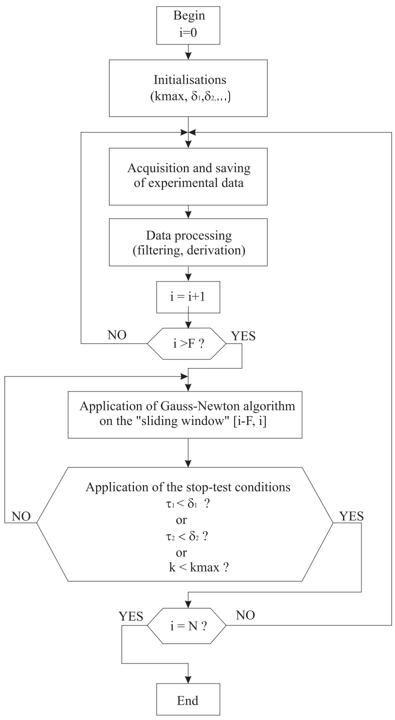

Figure 2 : Diagram of identification method

Remarks : The Numerical values used $(k\max, \delta_1, \delta_2, ...)$ will be given in section 5, with the experimental results. The damped Gauss-Newton algorithm is not developed here because it is classical in nonlinear programming {see for example (Norton, 1986; Walter and Pronzato, 1997)}.

5 Experimental results

After have mentioned experimental conditions, some significant numerical and graphical results will be given and analysed.

5.1 Conditions of experimentation

Different Pseudo random Binary Sequence (PBS) input signals are used on the identification process. For each manipulation, the volume connected to the i/p converter is equal to 75cm^3. The value of δ_1 is equal to 10^{-6} and the value of δ_2 is equal to 10^{-6}. The initial value of μ is equal to 1, and is adjusted so that $J(\Phi_{i+1}) < J(\Phi_i)$ (damped Gauss-Newton algorithm). For all the manipulations, the sampling time is equal to 2ms, the "sliding window" is composed of 100 points (0.2s), and kmax = 5.

5.2 Numerical results

The following table regroups some identification results. Column 1 represents the value of the criterion for on-line identification, column 2 represents the value of the criterion for off-line identification, and column 3 corresponds to the value of the criterion with weighted average parameters. This average parameters are calculated using off-line identified parameters, weighted with the accuracy of each off-line identification

	Criterion value (on-line identification)	Criterion value (off-line identification)	Criterion value (with average parameters)
PBS n°1	12.6643	14.2823	15.8532
PBS n°2	311.2988	273.6110	1241.2307
PBS n°3	46.3551	60.8253	319.0061
PBS n°4	37.9916	25.6090	186.3793

Table 1 : Identification results

5.3 Graphical Results

Figures 3-6 are results of some significant identifications.
Solid lines represent the response of the real process, (--) lines represent the simulated output with weighted average parameters, and (-.-) lines represent the results of simulation with on-line identified parameters. The values of the final criterion, calculated with all the points of the experimentation, and for both cases on-line identification and use of average parameters are given. We can note that for all the cases, the results of on-line identification are more accurate than results with average parameters. For the legibility of the graphical results, the response of the simulated output with off-line identified parameters is not given but results given in the table 1 permit to verify that off-line identification results are of the same order than on-line results.

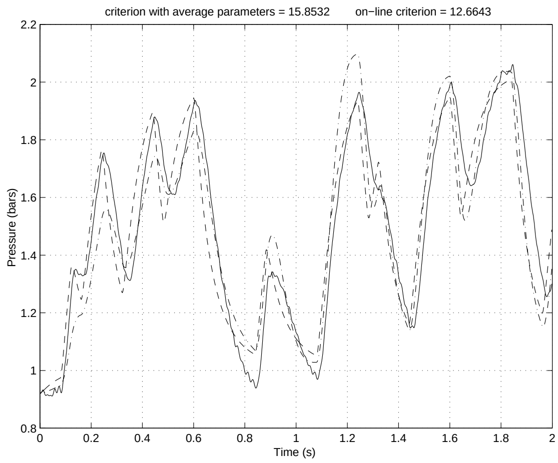

Figure 3 : Results for PBS n°1

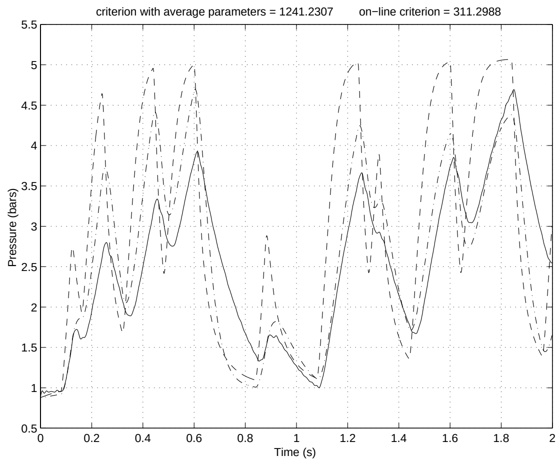

Figure 4 : Results for PBS n°2

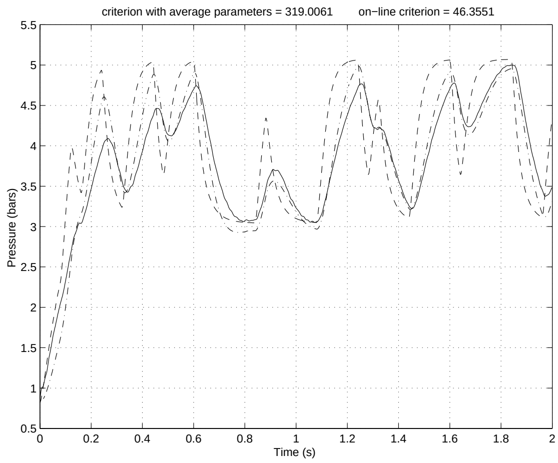

Figure 5 : Results for PBS n°3

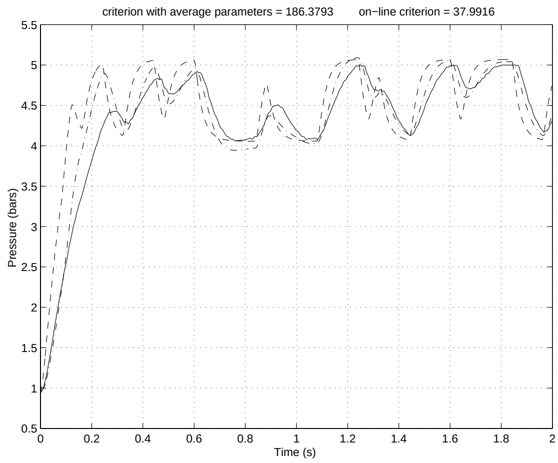

Figure 6 : Results for PBS n°4

5.4 Analysis of results

Some remarks must be deduced of the previous results :

1. The identification method gives quite good results. The response of the model of the system globally well tracks the output of the real system, and the results are generally more accurate using on-line identified parameters.

2. An improvement of on-line results can be obtained increasing the number of points of the sliding window, or increasing value of kmax, but our material configuration (Pentium) limits us. This algorithm will be soon implemented on a more efficient configuration (Pentium II), which allow us to increase the number of points of the sliding window, and allow more restrictive stop-tests, from which it follows that results of identification would be more accurate.

6 Conclusion, future works

The modification of a classical nonlinear programming algorithm (the algorithm used is a damped Gauss-Newton algorithm), in the aim to permit its use on-line has been developed. This modification is centred on the use of the flat differentially model of a process, from which solution is directly obtained without integration, which save considerable computation time. Some experimental results have been given, which show feasibility and efficiency of the method.

Present work deals with the improvement of accuracy of the method, working on numerical filtering and derivative algorithms, on the stop-tests of the optimization algorithm, on the limitation at each iteration of the variation of the value of the parameters (variation limited in percents regarding previous value of parameters, or average value).

Future works, and the objective of final work is to use this method in an adaptive control algorithm, on the i/p converter in a first time, then on the actuator (i/p converter + muscle), so we hope obtain an efficient control law, then implementation of this control law on the robots of the laboratory will be done.

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