Fast tuning of cascade control systems ⋆

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Abstract: In this paper, an algorithm for direct data-driven design of cascade control system is proposed and analysed. The procedure is based on the Virtual Reference Feedback Tuning (VRFT) approach but it allows to tune either the inner and the outer loops by means of a single set of experimental data. The main differences between the standard VRFT and the proposed approach are highlighted and analyzed. The design technique is finally applied on a micro-positioning control problem for Electro-HydroStatic Actuators (EHSAs).

Keywords: cascade control systems, VRFT, direct data-driven control

1. INTRODUCTION

In standard SISO feedback control schemes, the control variable is a function of the difference between the reference behaviour and the output signal. In these schemes, noise effect can be rejected only when they are already affecting the output signal, and then they are detectable. In such cases, it may happen that the overall behaviour is not satisfactory and therefore different solutions are required. Among these, cascade control systems (see Skogestad and Postlethwaite [1996]) are constituted by two loops: an inner loop aimed to reject all noise effects, and an outer loop with the purpose of tracking the reference signal. It is a general rule for the embedded loop to be much faster that the outer one for having accurate disturbance rejection.
The standard approach for cascade control system tuning is based on the knowledge of a mathematical model of the system. Such model is used to study the system dynamics, to understand which dynamics are negligible and then to design a suitable control law via model-based methodologies. In a data-driven setting, where a set of input-output data is available, the complete procedure for modeling the system and designing the feedback controllers may be costly and time-consuming in real industrial applications. For this reason, in Previdi et al. [2010] a model-free approach for cascade control system tuning has been proposed by means of the Virtual Reference Feedback Tuning (see Campi et al. [2002] for a detailed presentation of the methodology). The standard method allows to tune the two loops by performing two different experiments and using data to minimize a suitable approximation of a model reference criterion. Moreover, in Previdi et al. [2010] a preliminary idea for tuning the overall scheme with a single experiment is presented.
In this paper, such preliminary approach is analysed in detail and suitably modified in order to achieve better performance in terms of controller identification and noise rejection. The proposed technique is then studied in-depth for the case of servomechanism control design and it is applied to an Electro-HydroStatic Actuator (EHSA) prototype, a new generation of hydraulic actuator providing the main advantages of both mechanical and hydraulic actuators but able to reduce most of the drawbacks.
The cascade VRFT approach will be shown to be particularly appealing for this kind of control problems; furthermore, it will be experimentally proved that the resulting positioning system is even robust with respect to strong load variations.

The paper is organized as follows. In Section 2, preliminaries on standard VRFT is presented. Section 3 outlines the complete cascade VRFT methodology and presents the main advantages in applying such philosophy for servomechanism control. In Section 4, the EHSA architecture is presented and experimental results on a real benchmark are illustrated and commented. The paper is ended by some concluding remarks.

2. BACKGROUNDS ON VRFT

Consider a stable LTI discrete-time system $G(q)$, a class of controllers $\mathcal{C} = \{C(q,\theta)\ ,\ \theta \in \mathbb{R}^n\}$, and a given target closed-loop behaviour $M(q)$, as in Figure 1. The control

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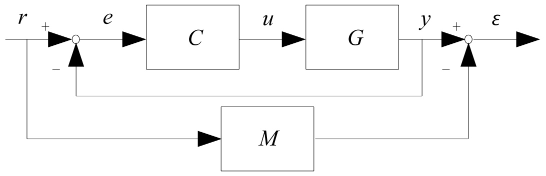

Fig. 1. Closed Loop Scheme and Model Reference Problem

aim is the minimization of the $\mathcal{L}_2$-norm of the modeling error:

$$J_{MR}(\theta) = \left\| \left(\frac{G(q)C(q,\theta)}{1+P(q)C(q,\theta)} - M(q) \right) W(q) \right\|_2^2 \qquad (1)$$

The ideal controller that guarantees a perfect model-matching is obviously given by

$$C_0(q) = \frac{1}{G(q)} \frac{M(q)}{1-M(q)}. \qquad (2)$$

The VRFT synthesis solves the model-reference problem, as formulated in (1), without any knowledge of the system and using only a set of available input/output measurements $\{u(t), y(t)\}_{t=1..N}$.

The main idea is taken from Guardabassi and Savaresi [1997] and Guardabassi and Savaresi [2001] and it is the so-called **"virtual-reference" principle** (consider $L(q)$ as the generic pre-filter for data): *the best controller with the requested structure is the one that minimizes the variance of the error between the filtered input signal* $u_L(t) = L(q)u(t)$ *and the input that the controller generates, when fed by* $e_L(t) = L(q)e_V(t) = L(z)\left(M(z)^{-1} - 1\right) y(t)$.

Formally, the cost criterion minimized by the VRFT algorithm is the following:

$$J_{VR}^N(\theta) = \frac{1}{N} \sum_{t=1}^{N} \left(u_L(t) - C(q,\theta) e_L(t) \right)^2 \qquad (3)$$

where N is the length of the data-set. In Campi et al. [2002], the authors demonstrate that, with a suitable choice of $L(q)$, the cost function (3) is a local approximation of the criterion (1) in the neighborhood of the minimum point.

Recent studies on the standard methodology can be found, *e.g.*, in Campestrini et al. [2009] and Formentin et al. [2011], while an application study is available, *e.g.* in Previdi et al. [2004].

3. CASCADE CONTROLLER DESIGN VIA VIRTUAL REFERENCE FEEDBACK TUNING

In the cascade control framework, the VRFT idea can be used to tune both the inner and the outer controllers starting from a single set of I/O measurements. The algorithm is first developed in a noiseless setting (see Subsection 3.1), while in Subsection 3.2 a brief technical analysis of the method for noisy data is provided. It should be remarked that the proposed method could be easily extended to multiple nested-loops. However, all the discussion will be focused on the two nested-loop structure without loss of generality for ease of explanation.

3.1 Noiseless setting

Consider the cascade control scheme in 2. Given the two reference models $M_i(q)$ of the inner loop and $M_o(q)$ of the outer loop, consider two families of linear proper controllers $\{C_i(q;\theta_i)\}$ and $\{C_o(q;\theta_o)\}$ and the set of data $u(t), y_i(t), y_o(t)_(t = 1, \ldots, N)$ being u(t) the control variable, $y_i(t)$ the output of the inner loop, $y_o(t)$ the output of the outer loop. The inner controller can be easily tuned by standard VRFT, since I/O data are completely available and no other requests are made on the loop but being as close as possible to the reference model $M_i(q)$. Concerning the outer controller, the approach must be different, since the input of the system to control is the reference $r_i(t)$ (see again Figure 2), that is not available (recall that measurements are collected open-loop). In Previdi et al. [2010], the reference signal for the inner loop is computed off-line as $r_i(t) = r_{iV}(t)$, where $r_{iV}(t)$ is the virtual signal for which it holds that: $y_i(t) = M_i(q) r_{iV}(t)$.

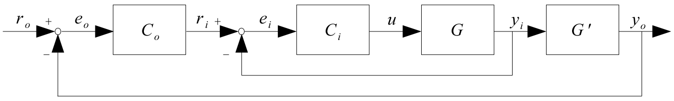

Fig. 2. Cascade control scheme with two nested loops.

If the inner controller is correctly parameterized with respect to the optimal controller, *i.e.* if the controller that brings (1) to zero belongs to the class $C_i(q;\theta_i)$, the so-computed reference is exactly the signal that would feed the inner loop in closed-loop working conditions. In this case, the outer controller can be tuned by simple VRFT procedure. On the other hand, in case of undermodeling, the actual inner loop might be different with respect to the reference model. In such situations, the input $r_{iV}(t)$ corresponding to the output $y_i(t)$ is no more close to the one given by the computation suggested in Previdi et al. [2010] and a different computation of $r_i(t)$ would be preferable. The reference signal can be computed by taking advantage of the fact that the inner controller design is independent of the outer synthesis. In detail, the input of the inner loop can be calculated as

$$r_i(t) = r_{iV}^*(t) = e_i(t) + y_i(t),$$

where the tracking error is fictitious and coming from the result of the inner design in the following way:

$$e_i(t) = C_i^{-1}(q;\theta_i) u(t).$$

With such a choice, $r_i(t)$ is exactly the signal that would feed the inner loop in closed-loop working conditions when the output is $y_i(t)$. Then, the outer controller can be easily found as result of VRFT synthesis, by using the set of I/O data $\{r_i(t), y_o(t)\}_{t=1,\ldots,N}$. It follows that this design procedure may encounter some problems only if the inner controller is non-minimum phase (NMP). In this case, the inverse of such system would produce a tracking error and a reference signal that are no more stationary and thus they cannot be used for identification purposes.

The algorithm can then be summarized as follows.

CASCADE VRFT ALGORITHM:

(1) Calculate:
The inner virtual reference $r_{iV}(t)$ such that

$$y_i(t) = M_i(q) r_{iV}(t)$$

the inner virtual tracking error

$$e_{iV}(t) = r_{iV}(t) - y_i(t)$$

the outer virtual reference $r_{oV}(t)$ such that

$$y_o(t) = M_o(q) r_{oV}(t)$$

the corresponding outer virtual tracking error

$$e_{oV}(t) = r_{oV}(t) - y_o(t)$$

(2) Filter the signals $e_{iV}(t)$ and $u(t)$ with a suitable filter $L_i(q)$, obtaining:

$$e_{iL}(t) = L_i(q) e_{iV}(t)$$
$$u_L(t) = L_i(q) u(t)$$

(3) Estimate the inner controller parameter vector and check that the resulting controller is a minimum-phase (MP) system:

$$\theta_i = \arg\min_{\theta_i} J_{VR}(\theta_i)$$

where

$$J_{VR}(\theta_i) = \frac{1}{N}\sum_{t=1}^{N}(u_L(t) - C_i(q;\theta_i)e_{iL}(t))^2 \qquad (4)$$

(4) If $C_i(q)$ is NMP, change the sampling time or the reference model. Otherwise, if $C_i(q)$ is MP, calculate the actual input signal $r^*_{iV}(t)$ for the inner loop

$$r^*_{iV}(t) = e_i(t) + y_i(t)$$
$$e_i(t) = C_i^{-1}(q;\theta_i)u(t)$$

(5) Filter the signals $e_{oV}(t)$ and $r^*_{iV}(t)$ with a suitable filter $L_o(q)$, obtaining:

$$e_{oL}(t) = L_o(q) e_{oV}(t)$$
$$r_{iL}(t) = L_o(q) r^*_{iV}(t)$$

(6) Estimate the outer controller parameter vector:

$$\theta_o = \arg\min_{\theta_o} J_{VR}(\theta_o)$$

where

$$J_{VR}(\theta_o) = \frac{1}{N}\sum_{t=1}^{N}(r_{iL}(t) - C_o(q;\theta_o)e_{oL}(t))^2 \qquad (5)$$

Notice that problems (4) and (5) are quadratic respectively in the two parameter vectors θ_i, θ_o and all the computations are directly performed on the measurement data, assumed that the filters $L_o(q)$ and $L_i(q)$ are given. Specifically, the optimal filters to be used in the design are

$$L_i(q) = \frac{M_i(q)(1 - M_i(q))W_i(q)}{U_i(q)}$$
$$L_o(q) = \frac{M_o(q)(1 - M_o(q))W_o(q)}{U_o(q)}$$

where $W_i(q)$ and $W_o(q)$ are the weighting functions for the inner and the outer loops; on the other hand, $U_i(q)$ is a model of the input signal such that $u(t) = U_i(q)w_i(t)$, where $w_i(t)$ is a white noise with unit variance and the input power density spectrum can be modeled as $\Phi_u(\omega) = |U_i(e^j\omega)|^2$. Similarly, $U_o(q)$ is a model of the inner virtual reference signal such that $r_i(t) = U_o(q)w_o(t)$, where $w_o(t)$ is a white noise with unit variance, so that the power density spectrum of this signal can be modeled as $\Phi_{r_i}(\omega) = |U_o(e^j\omega)|^2$. Details on the computation of the filters and the complete development of the algorithm can be found in Campi et al. [2002].

3.2 Noisy environment

In a noiseless setting, the cascade algorithm proposed in this paper is completely equivalent to the standard VRFT procedure, except for the number of experiments needed by the tuning procedure. As already underlined, the VRFT algorithm in Campi et al. [2002] requires one experiment for each controller tuning procedure, whereas the cascade VRFT performs the outer and inner design in "one-shot", by means of the same dataset. Equivalence between the two strategies can be verified by simply considering the second experiment of the standard algorithm. If the inner loop is fed by a reference signal equal to the virtual reference r_vV defined for the cascade procedure, the resulting outer controllers are completely identical.

In noisy environment, it is possible to highlight the difference between the methods and to underline how the additional information coming from the second experiment can be exploited.

Let introduce the noisy version of measured data

$$\tilde{y_i}(t) = y_i(t) + d_i(t)\ ,\tilde{y_o}(t) = y_o(t) + d_o(t),$$

where $d_i(t)$ and $d_o(t)$ are respectively the disturbances on the inner and the outer loop output signals. In this work, it will be assumed that no information is provided about noise models; moreover, $d_i(t)$ and $d_o(t)$ may also be correlated. This is the case of servomechanisms, where $y_i(t)$ is the (really measured) speed signal and $y_o(t)$ is the position signal derived by integration from $y_i(t)$.

In this noisy environment, the estimate of controllers is biased and unconsistent in both the standard and the cascade setting. However, the effect of noise on the outer controller is different in the two cases. As a matter of fact, if the outer controller is tuned by means of a second experiment, the reference signal $r_i(t)$ is user-defined and thus noiseless. It follows that the controller identification problem (5) is characterized by the presence of noise on the input only. If the cascade algorithm is employed, $r_i(t)$ is fictitious and computed starting from the noisy version of $y_i(t)$. Therefore, in this case, the identification issue resorts to a typical errors-in-variables (EIV) problem where both the input $\tilde{e}_V$ and the output $\tilde{r}_i$ are noisy (see Figure 3). Specifically, notice that the noise on $y_i(t)$ and the one on $r_i(t)$ coincide.

Intrumental Variable (IV) strategies can be employed to

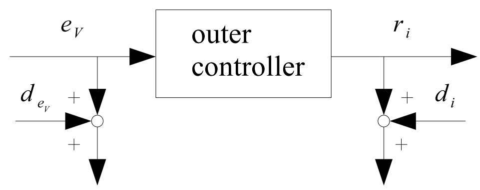

Fig. 3. Error-In-Variable equivalent scheme for outer controller tuning.

deal with noise in the EIV problem above (see Soderstrom [2007]). In detail, two solutions are proposed here for taking advantage of different experimental settings.

(1) **Repeated experiments:** If the system is available for experiments, one solution is to perform another open-loop data collection with the same input excitation. If the two experiments are uncorrelated, the new realization of $d_i(t)$ is uncorrelated with the previous $y_o(t)$ even if $d_o(t)$ and $d_i(t)$ are correlated. Therefore, consistent estimate of the outer controller is given by

$$\theta_o = \left[\frac{1}{N} \sum_{t=1}^{N} \zeta_L(t) \phi_L(t) \right]^{-1} \frac{1}{N} \sum_{t=1}^{N} \zeta_L(t) r_i(t), \quad (6)$$

where the regressor $\phi_L(t) = L_o(M_o^{-1} - 1)y_o(t)$ and the instrumental variable $\zeta(t) = L_o(M_o^{-1} - 1)y'_o(t)$, coming $y'_o(t)$ from the second experiment. Obviously, since the inner design is a standard VRFT problem, the second experiment can be used also for inner design as suggested in Campi et al. [2002].

(2) **Use of periodic data:** If the input signal is completely user-defined and periodic trajectories is feasible, the designer can avoid to perform other experiments, by employing the EIV method introduced in Soderstrom and Hong [2005] and extended for data-driven methods in van Heusden et al. [2011]. The method still resorts to IV optimization (6), but in this case $\zeta(t)$ is defined as $\zeta(t) = [\zeta_1(t)\zeta_2(t) \ldots \zeta_{n_p}(t)]$, where n_p is the number of periods in the dataset and

$$\zeta_j(t) = [\phi_{j+1}^T(t) \ldots \phi_{n_p}^T(t) \phi_1^T(t) \ldots \phi_{j-1}^T(t)],$$
$$\phi_j(t) = \phi_0(t) + d_{\phi,j}(t),$$

being $\phi_0(t)$ the noiseless regressor and $d_{\phi,j}(t)$ the disturbance on $\phi_0(t)$ in period j.

The first method can be suggeted if experiments are cheap and the input signal cannot guarantee periodicity. The second technique is the best if experiments are costly and the input signal is completely free. Notice that such second choice of IV also yields more statistically efficient solutions (see van Heusden et al. [2011] for exact expressions of the parameter covariance matrix).

3.3 P-PI strategy for motion control problems

The case of motion control of servomechanisms deserves a specific insight, as two peculiarities may be highlighted. In servocontrol, the inner loop is a speed control loop where $\{C_i(q; \theta_i)\}$ is the class of PI controllers, whereas the outer loop concerns the position signal and $\{C_o(q; \theta_i)\}$ is the class of proportional (P) controllers.
The following two properties hold.

(1) The gain and the integral time of the PI controller define a single zero in $C_i(q; \theta_i)$. In detail, since

$$\theta_i = [\theta_{i1}\ \theta_{i2}]^T = [K_i\ \ -K_iT_i],$$

it is sufficient to check that $|T_i| < 1$ to guarantee that $C_i^{-1}(q; \theta_i)$ is stable and that r_i is stationary. This can be done either after the inner synthesis (as in the general case) or better by formulating the inner control design as a constrained optimization problem.

(2) In most of the applications, the outer variable is simply often the integral of the inner one, multiplied by a gain corresponding to the transmission ratio and to the transformations of the measurement units. If the above assumption is true and the bandwidth of the inner closed-loop system is so high that the inner transfer function can be approximated with 1, then "a-priori" information on the structure of the process G' is available, that is

$$G'(q) = \frac{K}{q-1},$$

where obviously K is unknown and one-step delay has been added to model the discretization latency. In this situation, it is possible to choose $M_o(q)$ such that no underparameterization occurs; specifically, any reference model

$$M_o(q) = \frac{(1 - m_o)}{q - m_o}$$

with $|m_o| < 1$ can be achieved with a proportional controller to a good approximation. Obviously, perfect model-following is theoretically possible only in case where the inner closed-loop transfer function is a constant.

4. EXPERIMENTAL RESULTS ON AN ELECTRO-HYDROSTATIC ACTUATOR (EHSA)

The Electro HydroStatic Actuators (EHSA) (see *e.g.* Habibi and Goldenberg [2002]) technology is based on a closed-circuit hydraulic transmission, composed by a bidirectional pump, driven by an electrical motor, that regulates the oil movement and the pressure difference in the chambers of an hydraulic cylinder (Figure 4). The EHSA technology provides the main advantages of both Electro Hydraulic Actuators (EHA) and Electro Mechanic Actuators (EMA), reducing most of the drawbacks. Actually, the hydraulic circuit allows to reach an high force range and a very good reliability, as the EHA, while the presence of the coupled electric motor and pump makes possible an accurate control and positioning and large bandwidth dynamics, as the EMA. Moreover, the EHSA presents also an high energy efficiency, due to the fact that the pump works only on a movement demand and the actuating power is transferred by electricity (Power by Wire) instead of by the oil in the pipes (Power by Pipe). For these reasons, the EHSA has been lately applied in aeronautic sector, particularly in the critical safety applications (see *e.g.* Navarro [1997]).
The layout of the EHSA considered in this paper is based on a closed-circuit hydraulic transmission, which main components are (see Figure 4): a DC brushless electrical motor directly connected to a bidirectional fixed displacement gear pump; an hydraulic cylinder with a through rod connected to the pump; and a safety circuit, composed by a small tank, anticavitation and over pressure valves. The

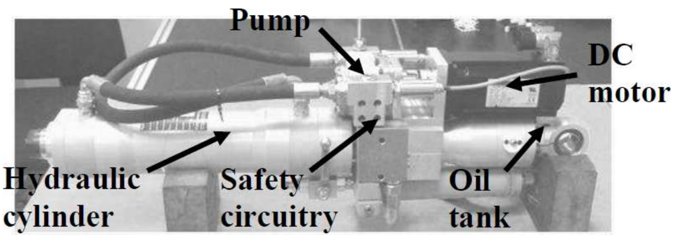

Fig. 4. The EHSA architecture.

specifications of the single components of the EHSA are reported in Table 5. The input-output open-loop experiment for control design is reported in Figure 6. A 1200-samples white noise reference current with zero mean value and variance of 5 A is used to excite the electric motor (the sampling time $T_s = 5\ ms$) and speed and position signals are collected. Since standard and cascade VRFT are to be compared, a second experiment is needed to tune the outer controller with the traditional method (see Figure 7). The speed reference signal is a 1000-samples white noise

Component	Features	Unit	Value
Electrical Motor	Power	[kW]	1.58
	Speed (max)	[rpm]	5000
	Torque (max)	[Nm]	16.1
Bidirectional Pump	Displacement	[cm3/rev]	3.7
	Speed (max)	[rpm]	4500
	Pressure (max)	[bar]	210
Hydraulic Cylinder	Stroke	[mm]	200
	Bore	[mm]	54
	Rod Diameter	[mm]	45

Fig. 5. Specification of the EHSA components.

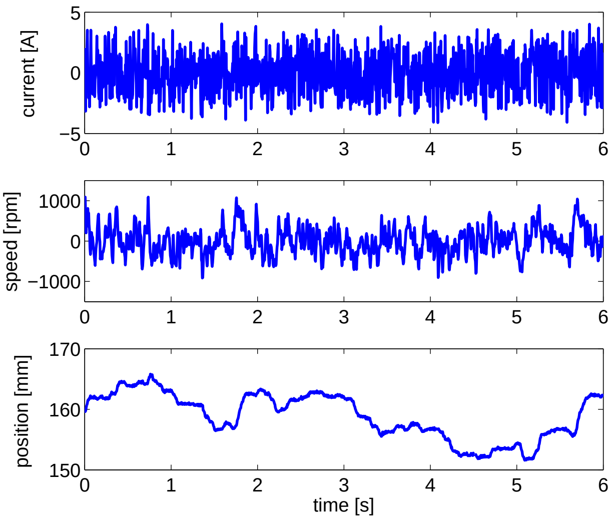

Fig. 6. Open-loop experiment.

with zero mean value and variance of 2400 rpm. It should

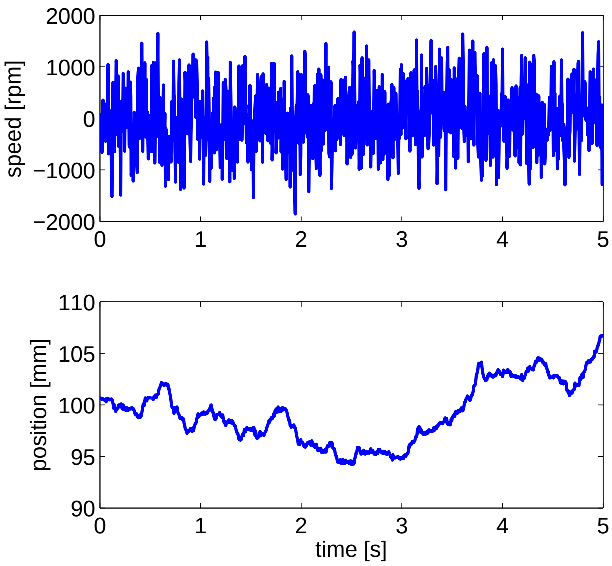

Fig. 7. Second outer-loop experiment for standard VRFT.

be underlined that such a choice of the input signal prevents the designer to employ EIV techniques with periodic data. However, this is not a problem, since in this case experiments are cheap and easy to perform. A “repeated experiments” procedure is then employed: 4 experiments for standard VRFT (2 for the inner and 2 for the outer loop) and 2 experiments for cascade VRFT. Nevertheless, it should be noticed that the Signal-to-Noise ratio is not critical in this application (see the power density spectrum of a 2 Hz sinusoidal speed signal in Figure 8).

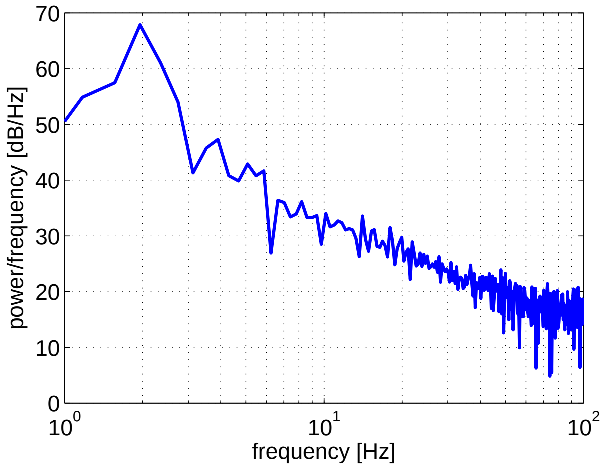

Fig. 8. Power density spectrum of a 2 Hz sinusoidal speed signal.

Consider to use the experiments above for identifying the control structures that best fit

$$M_i(q) = \frac{0.7154}{q - 0.2846}\ , \ M_o(q) = \frac{0.2222}{q - 0.7778},$$

i.e. the controllers that achieve 40 Hz inner bandwidth and 8 Hz outer bandwidth. Moreover, the weighting functions are chosen as

$$W_i(q) = \frac{0.7786}{q - 0.2214}\ , \ W_o(q) = \frac{0.2696}{q - 0.7304},$$

i.e. respectively a 48 Hz- and a 10 Hz- bandwidth transfer functions. The controllers resulting from the standard and the cascade VRFT procedures can be tested and compared by means *e.g.* of closed-loop square wave tests. In Figure 9, ideal and actual responses of speed and position for the cascade VRFT scheme are shown. The standard method obviously yields to the same speed behaviour, whereas it guarantees a (slightly) better behaviour concerning the position loop (see Figure 10). This fact is clearly due to the additional noise that affects the fictitious reference signal in the cascade VRFT algorithm (and that therefore leads to higher bias effect for finite number of data). Moreover, standard VRFT requires 2 experiment more to obtain unbiased results and therefore more information is practically available. Notwithstanding this, as SNR is high, the differences between the two methods is negligible. The overall control schemes have been tuned without additional load. In Figure 11, robustness of the position control system is tested with 30 kg and 60 kg load. Notice that even if there are some differences between the cascade VRFT controller and the one returned by the standard procedure, the overall behaviour shows good robustness to significant load variation.

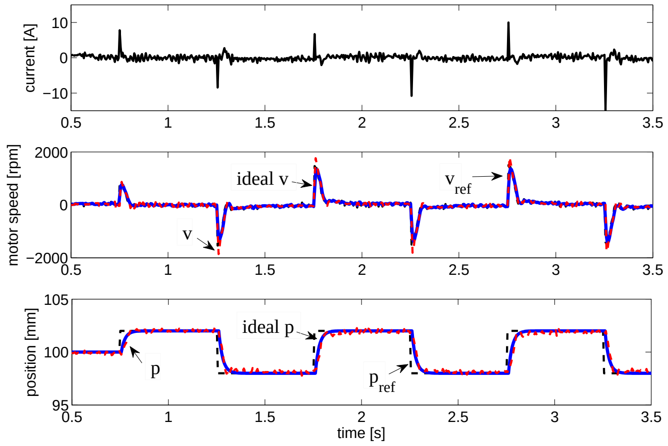

Fig. 9. Closed-loop response with cascade VRFT - in the speed plot all lines are almost overlapped.

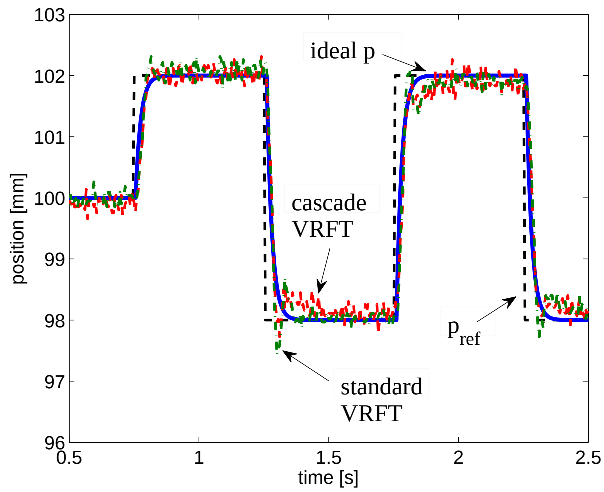

Fig. 10. Comparison between standard (dashed-dotted line) and cascade VRFT (dashed line).

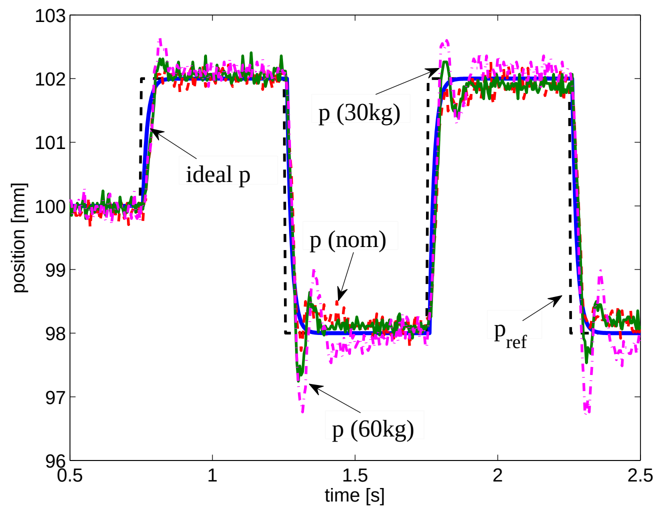

Fig. 11. Step responses of EHSA with cascade VRFT controller for different loads.

5. CONCLUSIONS

In this paper, it has been shown that the Virtual Reference rationale can be also successfully applied to the tuning problem of a cascade control system, with nested control loops. The proposed algorithm has been applied to the position control of an electro-hydrostatic actuator where the designed control system shows very good tracking performance and robustness to load variations. Future work will be focused on testing the cascade algorithm on different control applications.

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