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Data-based Design of High-performance Motion Controllers

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Abstract– **This paper presents a data-based design of a linear feedback controller which realizes desired closed-loop sensitivity and complementary sensitivity transfer functions. These transfer functions are specified via a single model-based performance cost. The data-based equivalent of this cost is derived, and its utility for the feedback design is demonstrated. A designer can prescribe the controller structure and complexity. Experimental results obtained in a direct-drive robot motion control problem show the quality of the design.**

I. Introduction

The data-based (DB) control field encompasses versatile research interests, approaches, and case studies. Roughly speaking, in DB techniques controllers are designed without explicitly making use of parametric models, but merely based on measured signals. Here we refer to a few DB methods: DB LQG control [1], unfalsified control [2], simultaneous perturbation stochastic approximation [3], iterative feedback tuning [4], disturbance-based control [5,6], virtual reference feedback tuning [7-9], etc.

In this paper, the motivations for the DB approach are simplified off-line design of high-performance motion controllers, and the direct supervision over the controller structure and its complexity. Our practice with model-based motion control confirms that closely accounting for empirical properties of the controlled system can significantly improve the control performance and the robustness against disturbances and parasitic dynamics [5,10,11]. However, the problem we commonly experience is the complexity of the design and of controllers that result from such designs. We reduce their complexity via model reduction to make them admissible for online implementation.

Here, we investigate if the control performance feasible with model-based motion controllers can also be realized with controllers designed using some DB method. The requirement is that the method must allow prescribing the controller structure and the complexity at the very beginning of the feedback design. A starting point was found in the virtual reference feedback tuning approach [7-9]. Starting from this, we derive our own DB method for controller design, which enables simultaneous shaping of the closed-loop sensitivity and the complementary sensitivity transfer functions. The derivation of the DB method will be explained in full detail. Its practical merits will be illustrated with experimental results obtained on a benchmark direct-drive robotic system.

Mathematical formulation of the DB controller design is given in the next section. Section III demonstrates DB design for the direct-drive robot and presents results of experimental evaluation. Conclusions are given at the end.

II. Mathematical Formulation

A. The Servo Set-up

The servo-system shown in Fig 1 illustrates the control set-up we are dealing with. The system consists of a LTI plant P and controller C. Here we assume a SISO one degree-of-freedom structure, although this is not essential for the method we will develop. The reference input is r, the control input is u, the plant output is y, and the error e is defined by:

$$e = r - y \,. \tag{1}$$

The desired control performance is specified via the desired closed-loop sensitivity and complementary sensitivity functions S_o and T_o, respectively. By means of S_o, a designer specifies the desired dynamics of the closed-loop system at low-frequencies, e.g., a minimum bandwidth requirement, integral control, and a level of error reduction. T_o facilitates specification of the maximum closed-loop bandwidth. It is also important for the robustness against resonances and noise at higher frequencies.

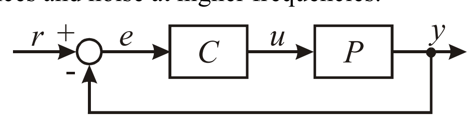

Fig.1. The servo set-up.

B. The Control Objective

The *objective* is to design a stabilizing controller C which closely realizes S_o and T_o. Ideally, controller C_o satisfies:

$$S_o = \frac{1}{1+PC_o}\,;\; T_o = \frac{PC_o}{1+PC_o}\,. \tag{2}$$

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Strictly speaking, there is no C_o satisfying both conditions of (2), unless $S_o + T_o = 1$ is fulfilled. This constraint implies that by specifying either S_o or T_o, the other transfer function is immediately found. However, the specified function must capture the desired closed-loop dynamics for both low and high frequency ranges. Although possible, specification of a single desired transfer function for the complete frequency scale usually is not a convenient task. Instead, a designer rather specifies both S_o and T_o, that are not necessarily in complement, but are rather idealistic requirements for the closed-loop dynamics at low and high frequencies, respectively. A C appropriately fulfilling the given control objective is the one which shapes the actual closed-loop sensitivity S $(=1/(1+PC))$ and the complementary sensitivity T $(=PCS)$ transfer functions such that $S \approx S_o$ and $T \approx T_o$, where the measure of distance from the ideal shapes is up to the designer.

C. Model-based v.s. Data-based Control Design

The problem posed is the previous subsection is well known in control theory. The existence of a stable controller that fulfils the control objective is addressed in [8] and is discussed in more details in [12]. To find such a controller, one can use a number of standard techniques. Among them, those based on optimization in an H_2 or H_∞ sense are typically applied; see e.g. [13,14]. These techniques are model-based, as they determine the appropriate C using some parametric representation of the plant. Although very effective for computing a C closely realizing the desired S_o and T_o, the model-based techniques usually feature a common problem: the generalized plant model uniquely defines the structure and complexity of the resulting controller. If this model is of high order, then the order of the resulting C is also high. As the controller complexity is an important factor for implementation, a designer often has to take special care to come up with a C which fulfils the given control objective and is also suitable for application. This is realized either by using generalized plants of restricted complexity, or by model reduction technique of the originally designed C.

In the next part we will present a data-based method that realizes the given control objective, but, contrary to the standard model-based techniques, also gives a designer the freedom to prescribe the controller structure and complexity at the very beginning of the control design. This is a direct consequence of using time-domain data to represent the plant dynamics, instead of resorting to some parametric model. The necessary data are signals obtained either by direct measurements on the plant, or they are synthetically generated using some plant model. It will be seen that the complexity of this model is not restricted, and that it is not necessarily a parametric one.

D. Required Data

Typical signals required for the data based control design are the input to the plant u and the corresponding plant output y. However, they are not the only choices. For instance, if the plant nominally operates in closed-loop (because of stability or other reasons), then any set of input and output signals that can recover information about the plant dynamics can be used. For the sake of clarity, in our presentation we will stick to u and y. Assume that these signals are observed at N discrete time instants T_s, $2T_s$, …, NT_s, where T_s is the sampling time. Consequently, two sets of data points are available $\{u(t)\}_{t=1,2,\ldots,N}$ and $\{y(t)\}_{t=1,2,\ldots,N}$, where t abbreviates tT_s. If observed from the real plant, it is irrelevant if $\{u(t)\}_{t=1,2,\ldots,N}$ and $\{y(t)\}_{t=1,2,\ldots,N}$ are obtained under open-loop or closed-loop operating conditions. The necessary requirement is that $\{u(t)\}_{t=1,2,\ldots,N}$ sufficiently excites the plant dynamics, so $\{y(t)\}_{t=1,2,\ldots,N}$ is rich around frequencies of interest for control, such as the crossover frequency [9]. When experimentally obtained, these signals can be corrupted with disturbances. This is addressed in subsection II *F*.

E. Data-based Control Design

The data-based (DB) control design will be formulated in the *Z*-domain. The two constraints on C_o given in (2) are replaced with a single one:

$$T_o(z) = C_o(z) S_o(z) P(z) . \tag{3}$$

where z is the complex variable from the *Z*-domain. The quest for a C which is close enough to C_o –once again, a metric is up to the designer– is highly facilitated if the search space is restricted to the class of linearly parameterized controllers

$$\{C(z,\boldsymbol{\theta})\} = \{C_p(z)\boldsymbol{\beta}^T(z)\boldsymbol{\theta}\} , \tag{4}$$

where $C_p(z)$ is the part explicitly assigned by the designer, and $\boldsymbol{\beta}^T(z)\boldsymbol{\theta}$ is the part to be tuned based on the observed data and on the performance specifications. The adopted controller class is used in a number of DB control designs, e.g. [2-4,7-9]. It is attractive since it facilitates, on one hand, explicit prescription of the controller structure and complexity, and, on another, it allows tuning the free parameters contained in $\boldsymbol{\theta}$.

The part of the controller assigned by the designer can reflect some a priory experience of the plant dynamics, e.g., observation of resonance frequencies and deterministic disturbances in the measured signals. If such effects are found, then the appropriate remedy can be directly integrated in the controller. For instance, notch filters can be applied to accomodate the resonances. Furthermore, $C_p(z)$ enables the designer to explicitly impose the desired controller effects, e.g. integral action, low-pass filtering characteristic, etc.

The tuning part of the controller consists of the vector of appropriately chosen basis functions $\boldsymbol{\beta}$, and of the vector of the tuning parameters $\boldsymbol{\theta}$:

$$\boldsymbol{\beta}(z) = [\beta_0(z)\ \beta_1(z)\ \ldots\ \beta_n(z)]^T,\ \ \boldsymbol{\theta} = [\theta_0\ \theta_1\ \ldots\ \theta_n]^T. \quad (5)$$

Unfortunately, there is no formalism yet developed for selecting the basis functions that will compose a controller which tuning can be guaranteed to achieve the control objectives. FIR (finite impulse response) filters are typically selected for the basis functions [2-4,7-9]. This selection is strongly motivated from system identification theory [15].

Within the selected class (4), one is interested in the tuning (set of $\boldsymbol{\theta}$) that suitably realizes the given control objective. By virtue of (3), an adequate controller tuning is obtained by minimizing the model-based (MB) cost function:

$$J_{\text{MB}}(\boldsymbol{\theta}) = \left\| (T_{\text{o}}(z) - C(z,\boldsymbol{\theta})S_{\text{o}}(z)P(z))W(z) \right\|_2^2, \quad (6)$$

where $\| \ \|_2$ denotes the standard H_2-norm, and W is a stable filter. As discussed in [9], this filter is chosen by the designer so as to emphasize the frequency regions where the desired S_{o} and T_{o} are low in magnitude: low frequencies for S_{o} and high frequencies for T_{o}. In these regions, large relative errors between $C(z,\boldsymbol{\theta})$ and $C_{\text{o}}(z)$ may have little impact on the integral H_2-norm cost (6) because of small S_{o} and T_{o}. Therefore, W is used as weighting to compensate for low magnitudes of S_{o} and T_{o}, which balances importance of all frequency regions in the cost (6).

The MB cost function (6) is minimized for all $\boldsymbol{\theta}$ when:

$$T_{\text{o}}(z) = C(z,\boldsymbol{\theta})S_{\text{o}}(z)P(z). \quad (7)$$

This condition can be considered as a definition of the filter, which can be used for processing the observed control input $\{u(t)\}_{t=1,2,\ldots,N}$:

$$T_{\text{o}}(z)u(t) = C(z,\boldsymbol{\theta})S_{\text{o}}(z)P(z)u(t). \quad (8)$$

Using the relation $y = Pu$, see Fig. 1, we can rewrite (8) as

$$T_{\text{o}}(z)u(t) = C(z,\boldsymbol{\theta})S_{\text{o}}(z)y(t). \quad (9)$$

The last expression induces a DB cost function, which facilitates tuning of the free parameters $\boldsymbol{\theta}$:

$$J_{\text{DB}}^N(\boldsymbol{\theta}) = \frac{1}{N}\sum_{t=1}^{N}[L(z)(T_{\text{o}}(z)u(t) - C(z,\boldsymbol{\theta})S_{\text{o}}(z)y(t))]^2. \quad (10)$$

Here, L is a stable filter which purpose is to ensure the equivalence between the MB and DB costs (6) and (10), respectively. The condition of equivalence can be derived using the same strategy as in the VRFT method [7-9], and it will be done later on in this subsection. Notice that only observed signals are used in the cost (10) and no plant model is required.

Since the considered controller class (4) is linear in the free parameters $\boldsymbol{\theta}$, the DB cost is quadratic in them. Thus, the global minimizer $\hat{\boldsymbol{\theta}}$ of the DB cost is found using the least-squares method [15]:

$$\mathbf{A}_N\hat{\boldsymbol{\theta}}^N = \mathbf{f}_N,\ \mathbf{A}_N = \sum_{t=1}^{N}\varphi(t)\varphi^T(t),\ \mathbf{f}_N = \sum_{t=1}^{N}\varphi(t)u_T(t),$$
$$\varphi(t) = \boldsymbol{\beta}(z)C_{\text{p}}(z)L(z)S_{\text{o}}(z)y(t),\ u_T(t) = L(z)T_{\text{o}}(z)u(t). \quad (11)$$

The superscript 'N' indicates that the tuning is based on N data points.

By recalling that

$$\|H(z)\|_2^2 = \frac{1}{2\pi}\int_{-\pi}^{\pi}\left|H(e^{j\Omega})\right|^2 d\Omega, \quad (12)$$

where Ω is the normalized angular frequency related with the actual ω via $\Omega = \omega T_s$, one may find a frequency-domain interpretation of the MB cost (6):

$$\begin{aligned} J_{\text{MB}}(\boldsymbol{\theta}) &= \frac{1}{2\pi}\int_{-\pi}^{\pi}\left|T_{\text{o}} - C(\boldsymbol{\theta})S_{\text{o}}P\right|^2|W|^2 d\Omega \\ &= \frac{1}{2\pi}\int_{-\pi}^{\pi}\frac{|P|^2}{|1+PC_{\text{o}}|^2}\left|C_{\text{o}} - C(\boldsymbol{\theta})\right|^2|W|^2 d\Omega. \end{aligned} \quad (13)$$

The argument $e^{j\Omega}$ is dropped for simplicity. A frequency-domain interpretation of the DB cost (10) is derived under standard assumptions that the observed signals are stationary and ergodic, and that the number of observed data points is sufficiently high ($N \to \infty$) for asymptotic convergence $J_{\text{DB}}^N(\boldsymbol{\theta}) \underset{N\to\infty}{\to} J_{\text{DB}}(\boldsymbol{\theta})$, where

$$\begin{aligned} J_{\text{DB}}(\boldsymbol{\theta}) &= E[\{L(z)[T_{\text{o}}(z)u(t) - C(z,\boldsymbol{\theta})S_{\text{o}}(z)y(t)]\}^2] \\ &= E[\{L(z)[T_{\text{o}}(z) - C(z,\boldsymbol{\theta})S_{\text{o}}(z)P(z)]u(t)\}^2] \\ &= E\left[\left\{\frac{L(z)P(z)(C_{\text{o}}(z) - C(z,\boldsymbol{\theta}))}{1+P(z)C_{\text{o}}(z)}u(t)\right\}^2\right]. \end{aligned} \quad (14)$$

By using Parseval's identity [15], one may find the frequency-domain counterpart of $J_{\text{DB}}(\boldsymbol{\theta})$:

$$J_{\text{DB}}(\boldsymbol{\theta}) = \frac{1}{2\pi}\int_{-\pi}^{\pi}\frac{|L|^2|P|^2\left|C_{\text{o}} - C(\boldsymbol{\theta})\right|^2}{|1+PC_{\text{o}}|^2}\phi_u(\Omega)d\Omega, \quad (15)$$

where the argument $e^{j\Omega}$ has been dropped again, and ϕ_u is the power spectral density (PSD) of the input signal $u(t)$.

The equivalence between (13) and (15) is established following the same reasoning as in the VRFT method:

1) If $C_{\text{o}}(z) \in \{C(z,\boldsymbol{\theta})\}$, then the minimizer $\overline{\boldsymbol{\theta}}$ of J_{MB} coincides with $\hat{\boldsymbol{\theta}}$ of J_{DB}, as they both correspond to C_{o}, no matter what the plant, the filters, and the desired transfer functions are. Thus, if the number N of data points is high enough, then the controller optimally tuned with respect to J_{DB} coincides with the optimal one with respect to J_{MB}.

2) If $C_{\text{o}}(z) \notin \{C(z,\boldsymbol{\theta})\}$, then only a suboptimal solution of the MB problem (6) is found. However, this suboptimal solution can still be determined using (11). A sufficient condition for this is:

$$|L|^2 = |W|^2 / \phi_u \,. \qquad (16)$$

If the filter L is chosen according to (16), then by virtue of (13) and (15) one obtains $J_{\mathrm{DB}}(\boldsymbol{\theta}) \equiv J_{\mathrm{MB}}(\boldsymbol{\theta})$, implying that $\hat{\boldsymbol{\theta}}$ coincides with $\overline{\boldsymbol{\theta}}$. A viable choice of the filter $L(z)$ is

$$L(z) = W(z)Q(z)\,,\ Q(z) = 1/U(z)\,,\ |U|^2 = \phi_u \,. \qquad (17)$$

The filter $Q(z)$ must be stable. As suggested in the VRFT method, $Q(z)$ can be obtained by fitting a parametric transfer function into the PSD of the observed input signal $u(t)$. Standard methods to obtain such a parametric fit are described in [15,16]. If u is white Gaussian zero mean noise with variance σ_n^2, then Q is equivalent to $1/\sigma_n$.

F. Effect of Disturbances

It is shown in [7] that disturbance effects in the observed signals can cause biased controller tuning. If a disturbance (noise) is a realization of a stochastic process, then its influence can be compensated as suggested in [7,8]: using the instrumental variable technique [15]. The indicated references provide detailed explanation of this technique. Unfortunately, the technique cannot help with deterministic disturbances. These disturbances are not problematic if their deterministic behavior can be understood. Knowledge of this behavior helps one to discriminate between disturbances and information relevant to plant dynamics, when processing empirical signals observed from the plant. If, however, the deterministic behavior is such complex that its understanding and mathematical description are too costly and time consuming, perhaps even impossible, then the designer should find another way to extract the relevant information about the plant dynamics. A simple but effective solution is to use signals synthetically generated from some plant model, instead of the signals obtained by direct measurements. This, of course, assumes that the model of sufficient quality is already available, which is not always true. If it is possible to use the synthetic data, then the influence of deterministic disturbances is safely avoided. In our case study, we resort to this solution when designing feedback controllers for the direct-drive robot. *Remark*: use of a model may remind on model-based approach; still, our design method is DB by nature, no matter if the empirical data are substituted with the synthetic ones, or not.

III. DB Design for the RRR Robot

The direct-drive robot with three revolute joints (RRR robot), shown in Fig. 2, is the subject of our case study. We refer to [17,18] for the kinematic and dynamic models. Due to direct-drive actuation, the robot dynamics is highly nonlinear and coupled, which impedes motion control of high performance. Their effects are reduced via a nonlinear compensation based on the robot rigid-body dynamic model, as explained in [10,11]. The robot dynamics that are not covered with this compensation are the responsibility of feedback controllers, that we typically design using H_∞ control theory [10,11]. For this paper, the feedback controllers were designed using the DB method presented in the previous section. Here, we will illustrate the DB feedback design for the 1st robot joint only. The designs for the other joints were carried-out in a similar way.

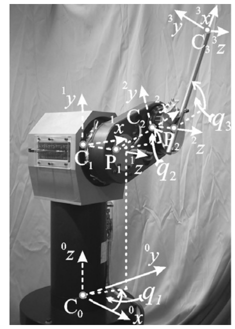

Fig. 2. The RRR robot.

Observation of signals from the robot must be done under closed-loop operating conditions (stabilization). Within the bandwidth (below 4 [Hz]) of the servo-system used for experiments, we achieve poor coherence [15,16] between the measured u and y. This problem is explained in more details in [11]. As a consequence, the observed signals cannot reliably represent decoupled robot dynamics at low frequencies. On the other hand, the robot dynamics is deterministic, but highly nonlinear and coupled, with significant friction effects. With the model-based control component we manage to reduce nonlinearity, but we hardly eliminate it. A consequence is that the online observed signals are always corrupted with residual nonlinear effects. Although deterministic, these effects are complex, and they can cause biased tuning of DB designed controllers. It appears, though, that the dominant nonlinearity is also in the lower frequency range, where we already experience the problem of poor coherence between u and y. Fortunately, at low frequencies the decoupled robot dynamics is rigid and can be represented with decoupled single inertias, i.e., decoupled double integrators [10,11]. Knowledge of the rigid dynamics can be used to avoid problems with empirical data at low frequencies. By using spectrum analysis techniques [15,16] we can determine frequency response functions (FRFs') of the decoupled robot dynamics. The method we apply is described in [11]. The determined FRFs' have incorrect shapes at low frequencies, because of the coherence problem and nonlinearities. However, these shapes can be corrected easily to match those of double integrators.

In Fig. 3 we show the FRF of the decoupled dynamics in the 1st robot joint, after it has been enforced to the correct shape at low frequencies. The Bode plot of the corresponding 15th-order parametric model $P(z)$ is also depicted. It should be noted that the given FRF represents the average joint dynamics, which was elaborated in [11]. A FRF, or the corresponding $P(z)$, can be used to represent a plant for which the feedback design should be carried out. Relevancy of such plant representations has been verified in all our previous model-based control designs [10,11]. Thus, it seems justified to use these representations for synthetic generation of signals u and y required by the DB method, which saves us from problems experienced with empirical signals at low frequencies.

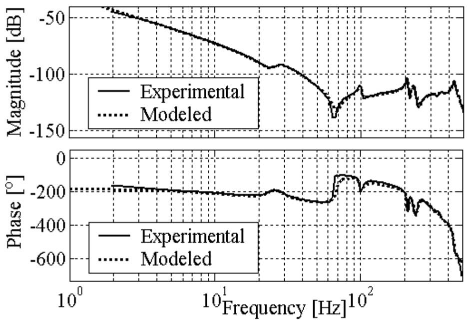

Fig. 3. Experimental and modeled Bode plots of the plant.

In Fig. 4, we present Bode magnitude plots of the desired sensitivity S_o and the complementary sensitivity T_o transfer functions. To indicate that S_o and T_o are not in complement, in the same figure we plot $1-S_o$, too. S_o was chosen such as to achieve high error reduction in the lower frequency range, while T_o ensures robustness against high-frequency resonances. At the beginning, the slope of S_o is +3, indicating that we are eager to achieve a single integrator in the resulting controller; the plant itself introduces double integral effect. The weighting filter $W(z)$ from the MB cost (6), which magnitude plot is also shown in Fig. 4, was chosen to adequately emphasize the lower and higher frequency ranges as discussed in subsection II *E*.

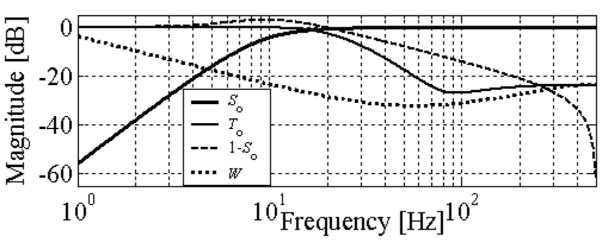

Fig. 4. The desired S_o and T_o, and the weighting filter W.

The DB controller design was carried out as described in subsection II. *E*. The necessary data was generated using the parametric model $P(z)$. The model was excited in open-loop with white Gaussian noise of zero mean and variance $\sigma_n = 150$. The excitation and the corresponding model output were observed with a sampling time of $T_s = 1$ [ms]. The number of collected data points was $N = 2^{15}$. The *L*-filter from the DB cost (10) was chosen as in (17), with $Q = 1/\sigma_n$. The prescribed structure of the controller $C(z, \boldsymbol{\theta})$: $C_p(z)$ was the product of one integrator (thus directly enforced in the controller structure) and two notch filters; the notches were based on our experience of resonances at 28 [Hz] and 98 [Hz] in the position measurements from the 1st robot joint; we used 12 FIR filters as the basis functions: $\boldsymbol{\beta}^T(z) = [1,\ z,^{-1}\ z,^{-2} \dots,\ z^{-12}]$; hence, 13 tuning parameters $\boldsymbol{\theta} = [\theta_0, \theta_1, \theta_2, \dots, \theta_{12}]^T$ were induced. The total order of 16 was intentional; this is the order of motion controllers of satisfactory performance we obtain after model reduction of 26th-order controllers resulting from model-based designs [10,11]. As criteria for the quality of the controller $C(z, \hat{\boldsymbol{\theta}}^N)$ resulting from our DB design (our measure of distance from C_o), we evaluated how close the achieved sensitivity function $(1/(1+P(z)C(z,\hat{\boldsymbol{\theta}}^N))$ and its complement (complementary sensitivity) are from S_o and T_o, respectively. We accept maximum peaking in the sensitivity of 6 [dB] [5]. Finally, $C(z, \hat{\boldsymbol{\theta}}^N)$ must be stabilizing for the plant in closed-loop. This was evaluated using the Nyquist criterion applied on the product between the plant's FRF and $C(z, \hat{\boldsymbol{\theta}}^N)$.

The parameters $\hat{\boldsymbol{\theta}}^N$ were computed using (11). The Bode plot of the resulting controller is shown in Fig. 5. By inspection of the plot, one notices that the integral action was achieved, and that effects of the enforced notches are present in the controller. Apart from the enforced ones, several other notch effects are also obvious. Induced by the resonances in the plant dynamics (see Fig. 3), these effects were created by the tuning part of the controller $\boldsymbol{\beta}^T(z)\boldsymbol{\theta}$. Bode magnitude plots of the achieved sensitivity and complementary sensitivity transfer functions are shown in Fig. 6, together with the corresponding desired transfer functions. The achieved transfer functions were computed based on the plant FRF data and $C(z, \hat{\boldsymbol{\theta}}^N)$. Similarities between the plots in the frequency ranges of interest are in agreement with our criteria, the peaking in the sensitivity is below 6 [dB], and the controller passed the stability test. Therefore, our requirements for the quality of the design have been met.

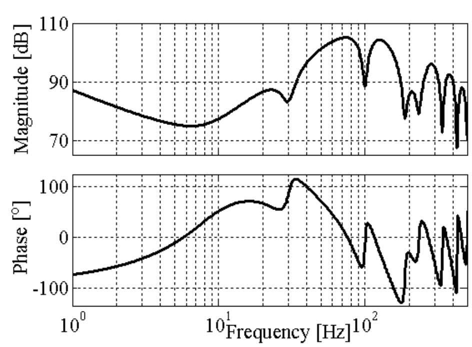

Fig. 5. The controller designed via the DB method.

As the final step, we practically implemented the controllers designed for all three joints to carry out some experimental assessments of the design. Because of the limited space, here we present only results obtained for the motion task shown in Fig. 7. In this task, each robot joint has to be displaced for π [rad] in 1 [s], with zero initial/terminal speed and acceleration. Such a vicious movement requires the full authority of the drives, and it was experimentally realized using the designed controllers. The achieved position errors are shown on the left in Fig. 8: the errors in joints 1 and 2 stay within the range $[-10^{-3}, 10^{-3}]$ [rad], and in joint 3 the error is twice that of the first two. The obtained accuracy is very good for a direct-drive robot. To evaluate if the notch effects were fruitful, on the right in Fig. 8 we plot *cumulative power spectra* (CPSs–cumulative sums of signals' power spectral densities). By inspection of these plots, we notice that the dominant energy of the tracking error is in the lower frequency range, which is the range of the reference trajectory shown in Fig. 7. Outside this range, abrupt changes in the slopes of the error CPSs are not visible, which means that no resonance was excited during the robot motion. Similar high accuracies without resonance effects were achieved in other motion tasks, too. Having this in mind, we can claim that the controllers resulting from our DB design were capable to realize motion control of high performance.

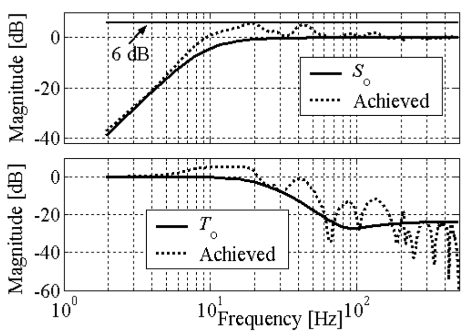

Fig. 6. The reference and realized closed-loop transfer functions: (top) sensitivity, (bottom) complementary sensitivity.

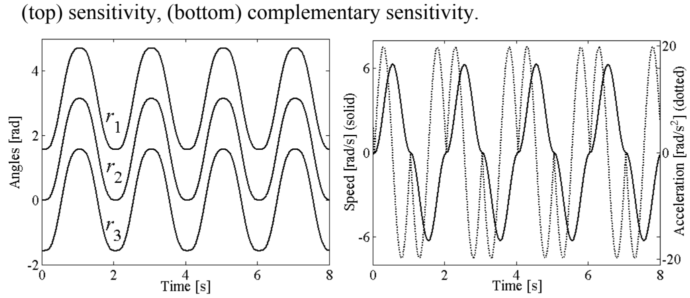

Fig. 7. The experimental motion task.

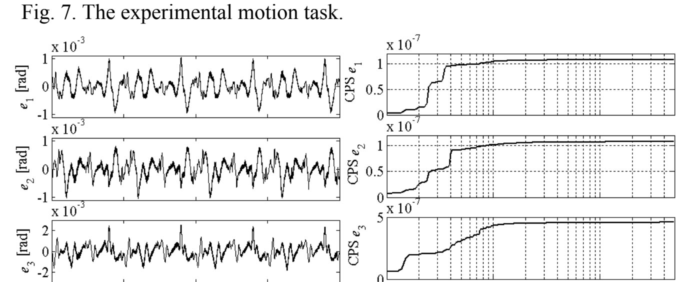

Fig. 8. Left: experimental position errors; right: cumulative power spectra.

IV. Conclusion

This paper presents another data-based (DB) method for controller design that enables simultaneous shaping of the closed-loop sensitivity and the complementary sensitivity transfer functions. Supported by the virtual reference feedback tuning methodology, the DB method finds its own way towards possible applications. The method is tested for a motion control problem. In this problem, the method is verified to be capable to tune controllers of adopted structure and complexity such that the motion control of high performance is realized. The method was successfully benchmarked on a direct-drive robot. Our next objective is to overcome the need for the synthetically generated data in the DB design of the robot motion controllers. The target is a design based on empirically observed signals, only. We investigate two possibilities: a) organization of a dedicated experiment to improve coherence between the robot input and output signals in the complete frequency range of interest, and, b) incorporating the influence of nonlinear disturbances into the DB controller design. We are also eager to achieve a stability test compatible with our DB method.

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