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Robust feedforward design for a two-degrees of freedom controller

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Abstract

In this paper we address the problem of designing the feedforward block of a two degrees of freedom controller in the case of single input single output (SISO) discrete-time linear systems with model uncertainty. In this work the design of the feedforward filter is formulated as a robust model matching problem. First, a closed form solution of the optimal noncausal filter, which minimizes the worst-case model matching error for each $\omega \in [0, 2\pi]$, is obtained. Then, suitable rational stable approximations of the optimal solution are derived either by means of causal filters or, when a preview of the reference signal is available, by means of noncausal FIR filters. The efficiency of the proposed method is tested on a simulated example.

Keywords: Two degrees of freedom; Robust control; Feedforward

1. Introduction

The paper deals with the problem of designing the feedforward block of a discrete-time two degrees of freedom control system. Two degrees of freedom design is a well known and widely used technique when both reference tracking and disturbance attenuation performances are required (see, e.g., [5,11]). It is well known that when there is no model uncertainty the design of the loop controller K and the feedforward filter Q (see Fig. 1) can be independently addressed without affecting achievable performances [11]. However, that is not true in the presence of modelling error. Since the joint synthesis of K and Q might become a difficult task, the design is usually still performed in two independent stages (see, e.g., [4,6]), which is also the approach taken in this work. Limebeer et al. in [6] design the feedback controller using the H_∞ loop shaping approach developed by McFarlane and Glover in [7]. Then, taking into account the model uncertainty in the multiplicative input form, they design the feedforward filter using H_∞ optimization via γ-iteration. Giusto and Paganini in [4] formulate the feedforward filter design in the presence of model uncertainty as a minimization of a linear functional subject to an infinite number of convex constraints. They provide approximate solutions derived either simplifying the original problem to one with a finite number of convex constraints through frequency gridding or optimizing over the span of a set of basis functions. In paper [1,3] the use of a feedforward controller based on the inversion of the nominal plant model is investigated. In [1] Devasia deals with the case of uncertain multi-input multi-output linear systems. He provides conditions, in terms of bounds on the size of the plant unstructured uncertainty, under which the use of inversion-based feedforward controller leads to tracking performances better than those achievable using only the feedback controller. The same problem is considered by Faanes and Skogestad in [3] for the case of SISO linear systems affected by parametric uncertainty.

In this work the design of robust two degrees of freedom controllers for the case of SISO discrete-time linear systems is considered. An uncertain model for the plant is assumed to be given in the form of an additive model set. On the basis of such a model set, the loop controller K which satisfies loop requirements can be designed exploiting standard robust control techniques. Here we focus on the design of the feedforward filter which is formulated as an original robust model-matching

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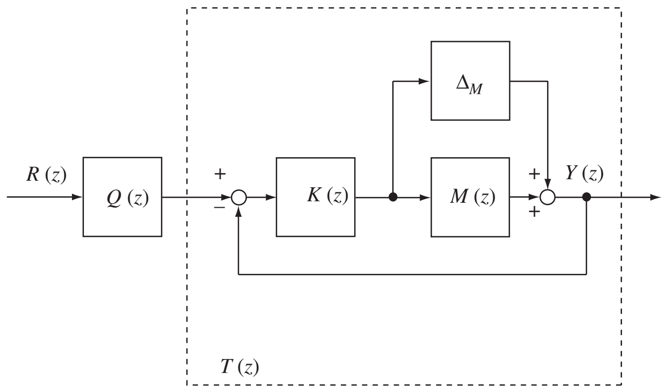

Fig. 1. Two degrees of freedom configuration in the presence of additive model uncertainty Δ_M.

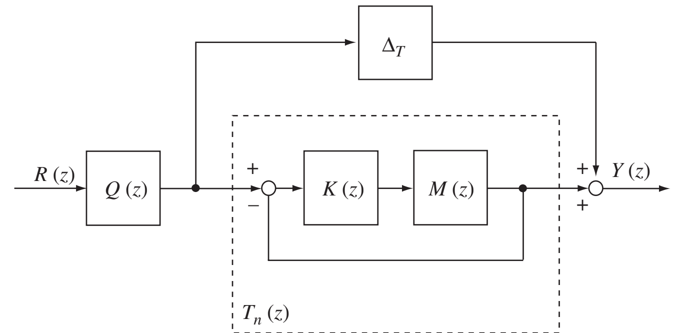

Fig. 2. Two degrees of freedom configuration in the presence of additive uncertainty on the complementary sensitivity T.

problem solved in two stages. First, in Section 2, the feedforward design is performed minimizing the worst-case model matching error at each $\omega \in [0, \pi]$ and a closed form optimal solution is provided. The obtained optimal filter $Q^*(\omega)$ is shown to be cascade connection of causal stable LTI system and a band-stop ideal, thus inherently noncausal, filter. Then, in Section 3, a method for the computation of a rational stable approximations $\hat{Q}(z)$ of the optimal solution is proposed. As far as a preview of the reference signal is available (that is the case in a number of real applications) we can compute a stable rational noncausal approximated filter which provides the best matching of the frequency response of the optimal filter among the class of noncausal finite impulse response (FIR) of a given order. By choosing the order large enough, the approximation error can be arbitrarily reduced since an ideal filter can be approximated with arbitrary accuracy in the mean-square sense by a (noncausal) FIR filter. Otherwise, when the reference preview is not available, a causal approximation of the optimal filter is computed which provides the best matching of the frequency response of the optimal filter among the class of causal FIR of given order. Finally, in Section 4, the effectiveness of the design procedure is shown by means of a simulated example.

2. Robust model-matching design

In this section the design of the feedforward filter is formulated as a worst-case model matching problem and the main result, i.e., the characterization of the optimal solution, is given. Here we consider discrete-time linear SISO systems described by their transfer functions. With a slight abuse of notation, $H(\omega)$ stands for the frequency response $H(e^{j\omega})$ of the generic system described by the transfer function $H(z)$.

An uncertainty model set $\mathscr{M}_M$ of the plant is assumed to be described by

$$\mathscr{M}_M(M, W_M) = \{(M(z) + \Delta_M(z)) \in \mathscr{S}: |\Delta_M(\omega)| \leqslant W_M(\omega)\ \forall \omega \in [0, \pi]\}, \tag{1}$$

where $\mathscr{S}$ is the Banach space of causal SISO linear time-invariant discrete-time BIBO-stable dynamical systems; $M(z)$ is a real rational model, $W_M(\omega)$ is a given function bounding the modelling error. On the basis of such a model set it is supposed that a robust controller $K(z)$, which satisfies loop requirements, has been previously designed. Given such a controller, an uncertainty model set $\mathscr{M}_T$ for the complementary sensitivity $T(z)$ can be described by (see Fig. 2)

$$\mathscr{M}_T(T_n, W_T) = \{(T_n(z) + \Delta_T(z)) \in \mathscr{S}: |\Delta_T(\omega)| \leqslant W_T(\omega)\ \forall \omega \in [0, \pi]\}, \tag{2}$$

where $T_n(z)$ is a n-order real rational model, $W_T(\omega)$ is a given function bounding the modelling error. Such a model set can be evaluated exploiting properties of the linear fractional transformation which exactly maps (i.e., with no conservatism) $\mathscr{M}_M$ in $\mathscr{M}_T$ as described in [2]. In the rest of the paper we assume that

$$|M_r(\omega)|=0\ \ \forall \omega \in \Gamma \quad \text{where } \Gamma=\{\omega \in [0, \pi]: |T_n(\omega)|=0\}, \tag{3}$$

that is, we assume that the reference model and the nominal model share the same zeros on the unit circle.

Given a discrete-time reference model $M_r(z)$ and the complementary sensitivity function belonging to the uncertainty model set $\mathscr{M}_T(T_n, W_T)$, we consider for any $\omega \in [0, \pi]$ the following worst-case model matching problem:

$$\begin{aligned} Q^*(\omega) &\doteq \arg\min_{Q(\omega)} \sup_{T \in \mathscr{M}_T} |Q(\omega)T(\omega) - M_r(\omega)| \\ &\doteq \arg\min_{Q(\omega)} \mathrm{WME}(\omega, Q). \end{aligned} \tag{4}$$

In the rest of the paper we refer to $\mathrm{WME}(\omega, Q) \doteq \sup_{T \in \mathscr{M}_T} |Q(\omega)T(\omega) - M_r(\omega)|$ as to the worst-case matching error. Note that, for a given Q, one gets

$$\mathrm{WME}(\omega, Q) = |Q(\omega)T_n(\omega) - M_r(\omega)| + |Q(\omega)|W_T(\omega) \tag{5}$$

as shown in Fig. 3. The following proposition provides the solution of the optimization problem (4).

Proposition 1. *Given the reference model $M_r(z)$ and the uncertainty model set $\mathscr{M}_T$, the solution $Q^*(\omega)$ of problem* (4) *is*

$$Q^*(\omega) = \begin{cases} M_r(\omega)/T_n(\omega) & \forall\, \omega: W_T(\omega) \leqslant |T_n(\omega)|, \\ 0 & \forall\, \omega: W_T(\omega) > |T_n(\omega)|. \end{cases} \tag{6}$$

In order to prove Proposition 1 the following Lemma is introduced.

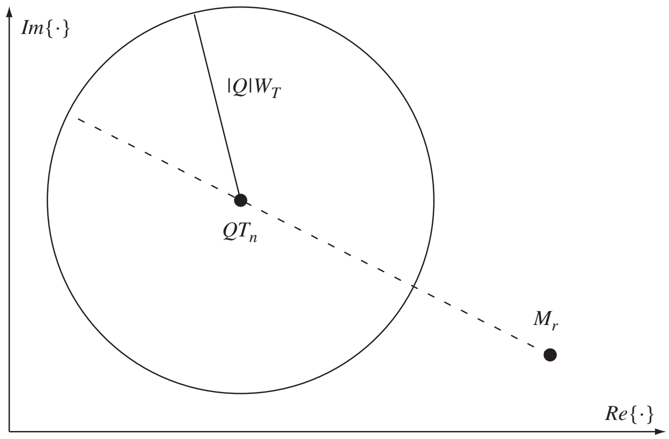

Fig. 3. Worst-case matching error WME (dashed segment) at fixed frequency ω.

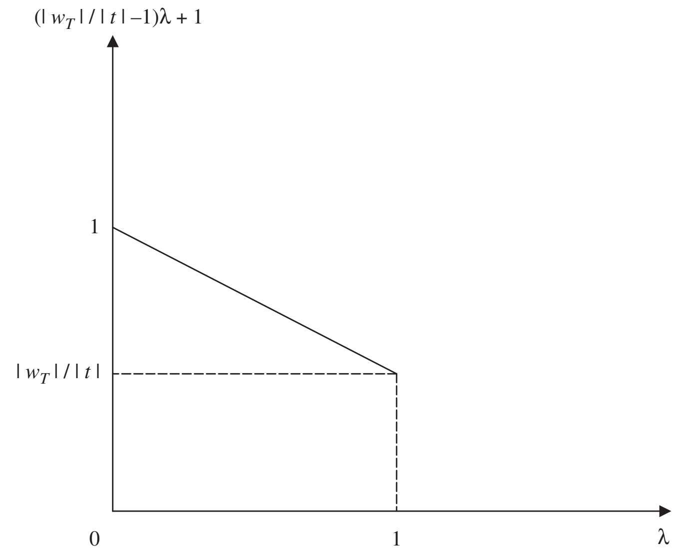

Fig. 4. Factor $(|w_T|/|t|-1)\lambda+1$ for $\lambda \in [0,1]$.

Lemma 1. *Let $t, m, w \in \mathbb{C}$ with $|t|+|w_T| \neq 0$ and $J:\mathbb{C} \to [0,+\infty)$ such that $J(q)=|qt-m|+|q||w_T|$. Then,*

$$\arg\min_q(J) = \begin{cases} 0 & \text{if } |w_T|/|t|>1 \\ & \text{or } t=0, \\ m/t & \text{if } |w_T|/|t|<1, \\ \{q : q=\lambda m/t,\ \lambda \in [0,1]\} & \text{if } |w_T|/|t|=1. \end{cases} \tag{7}$$

Proof. If $t=0$, $|w_T|>0$ and it is easy to see that $q=0$ attains the minimum value for $J(q)$; so let us suppose that $t \neq 0$.

$$J(q)=|qt-m|+|q||w_T|=|t||q-m/t|+|w_T||q-0|.$$

This mean that $J(q)$ is the weighted sum of the distances $|q-m/t|$ and $|q-0|$ with nonnegative weights $|t|$ and $|w_T|$, respectively. So, if q minimizes $J(q)$, then q must lay in the segment defined by m/t and 0. Thus, $q=\lambda m/t$ with $\lambda \in [0,1]$ and $J(q)=|t||\lambda m/t-m/t|+|w_T||\lambda m/t|$.

By working with this expression for $\lambda \in [0,1]$, it results

$$J(q)=|m|((|w_T|/|t|-1)\lambda+1).$$

The factor $(|w_T|/|t|-1)\lambda+1$ is an affine function of $\lambda \in [0,1]$ through points $(0,1)$ and $(1,|w_T|/|t|)$ (Fig. 4). The thesis of the lemma follows from the discussion of whether $|w_T|/|t|>1$ or $|w_T|/|t|<1$. □

Proof of Proposition 1. The proof is straightforwardly derived from Eq. (7) of Lemma 1 if we put $t=T_n(\omega)$, $m=M_r(\omega)$, $w_T=W_T(\omega)$, $q=Q^*(\omega)$, $J=\mathrm{WME}(\omega, Q^*(\omega))$ and $\lambda=1$. □

Remark 1. If we define $\Omega=\{\omega \in \Re : W_T(\omega)/|T_n(\omega)|>1\}$, Proposition 1 shows that $\forall\omega \notin \Omega$, the optimal solution $Q^*(\omega)$ coincides with the solution of the problem in the uncertainty-free case, i.e., the nominal filter $Q_n(\omega)=M_r(\omega)/T_n(\omega)$, while $\forall\omega \in \Omega$ the optimum is achieved turning off the feedforward controller. Thus, the optimal filter Q^* can be described as $Q^*(\omega)=Q_n(\omega)Q^*_\Omega(\omega)$ where Q_n is the nominal filter and $Q^*_\Omega(\omega)$ is the following band-stop ideal filter:

$$Q^*_\Omega(\omega)=\begin{cases} 1 & \forall\,\omega \notin \Omega, \\ 0 & \forall\,\omega \in \Omega. \end{cases} \tag{8}$$

Since the Paley–Wiener Theorem (see, e.g., [9]) implies that any ideal filter is noncausal, we conclude that Q^* is a noncausal filter.

Remark 2. Thanks to the assumption of Eq. (3) in Section 2, the optimal filter Q^* belongs to $\mathscr{L}_\infty$.

Since the optimal filter Q^* minimizes $\mathrm{WME}(\omega, Q)$ for each ω it is trivial to show that it minimizes also the worst-case model-matching error both in the $\mathscr{L}_\infty$ and the $\mathscr{L}_2$ norm, i.e.:

$$Q^*=\arg\min_{Q\in\mathscr{L}_\infty}\sup_{T\in\mathscr{M}_T}\|Q(\omega)T(\omega)-M_r(\omega)\|_\infty, \tag{9}$$

$$Q^*=\arg\min_{Q\in\mathscr{L}_\infty}\sup_{T\in\mathscr{M}_T}\|Q(\omega)T(\omega)-M_r(\omega)\|_2. \tag{10}$$

3. Approximation of the optimal filter

In Section 2 the optimal solution of the considered robust model-matching problem has been provided. The obtained optimal filter $Q^*(\omega)$ is given by the cascade connection of the nominal filter $Q_n(\omega)$ and a band-stop ideal filter which, as well known, cannot be implemented in practice. In this section the problem of computing a rational stable approximation $\hat{Q}(z)$ of the optimal filter $Q^*(\omega)$ is addressed. Remark 1 suggests that $\hat{Q}(z)$ should be looked for among the class of noncausal system. More precisely, we consider the following class of LTI stable discrete-time noncausal FIR:

$$\mathscr{C}^\gamma_{\mu\nu}=\left\{Q_{\mu\nu}(z)=\sum_{k=-\mu}^{\nu}h_k z^{-k} : \left|\frac{\mathrm{d}Q_{\mu\nu}(\omega)}{\mathrm{d}\omega}\right| \leqslant \gamma\ \forall\omega\right\}. \tag{11}$$

The set $\mathscr{C}_{\mu\nu}^{\gamma}$ is the class of the linear noncausal FIR filters of order $\mu+\nu$ which magnitude of the frequency response derivative is bounded by γ. For $\gamma=\infty$, $\mathscr{C}_{\mu\nu}^{\gamma}$ becomes the set of the noncausal FIR of order $\mu+\nu$, while for $\mu=0$ one gets the class of causal FIR of order ν.

The following procedure for the design of the approximated filter $\hat{Q}(z)$ is proposed. First (i), exploiting Proposition 1, the optimal filter $Q^*(\omega)$ is computed on a set of frequencies ω_k, $k=1,2,\ldots,N$ which suitably grids the interval $[0,\pi]$. Then (ii), for $\gamma=\infty$ and fixed μ and ν, a rational stable approximation $\hat{Q}_{\mu\nu}(z)=\sum_{k=-\mu}^{\nu}\hat{h}_k z^{-k}\in\mathscr{C}_{\mu\nu}^{\gamma}$ of $Q^*(z)$ is computed through the minimization of a weighted norm of the error between the frequency responses of the two filters $\hat{Q}_{\mu\nu}(z)$ and $Q^*(z)$. More specifically, the approximated filter is obtained as solution of the following optimization problem:

$$\hat{h}=\arg\min_{Q_{\mu\nu}\in\mathscr{C}_{\mu\nu}}\|W(y-F_N h)\|_2, \tag{12}$$

where $\|\cdot\|_2$ is the vector ℓ_2-norm, $\hat{h}=[\hat{h}_{-\mu}\ldots\hat{h}_{-1}\hat{h}_0\ldots\hat{h}_\nu]$ and $h=[h_{-\mu}\ldots h_{-1}h_0\ldots h_\nu]$ are the samples of the impulse response of filters $\hat{Q}_{\mu\nu}(z)$ and $Q_{\mu\nu}$, respectively, W is a diagonal weighting matrix accounting for the desired tolerance at different frequencies ω_k, and:

$$y=[y_1\cdots y_N]^{\mathrm{T}}\in R^{2N\times 1},$$

$$y_k=[\mathrm{Re}(Q^*(\omega_k))\mathrm{Im}(Q^*(\omega_k))]^{\mathrm{T}}\in R^{2\times 1},$$

$$F_N=[\Omega^{\mathrm{T}}(\omega_1)\cdots\Omega^{\mathrm{T}}(\omega_N)]^{\mathrm{T}}\in R^{2N\times(\mu+\nu+1)},$$

$$\Omega(\omega_k)=\begin{bmatrix}\mathrm{Re}(\Psi(\omega_k))\\ \mathrm{Im}(\Psi(\omega_k))\end{bmatrix}\in R^{2\times(\mu+\nu+1)},$$

$$\Psi(\omega_k)=[\mathrm{e}^{\mathrm{j}\mu\omega_k}\cdots\mathrm{e}^{\mathrm{j}2\omega_k}\mathrm{e}^{\mathrm{j}\omega_k}1\mathrm{e}^{-\mathrm{j}\omega_k}\mathrm{e}^{-\mathrm{j}2\omega_k}\cdots\mathrm{e}^{-\mathrm{j}\nu\omega_k}]\in\mathscr{C}^{1\times(\mu+\nu+1)},$$

where Re(·) and Im(·) stand for the real and the imaginary parts, respectively.

The computed $\hat{Q}_{\mu\nu}(z)$ is the filter which provides the best matching of the frequency response of the optimal filter among the class of noncausal FIR of order $\mu+\nu$. By choosing μ and ν large enough, the approximation error can be arbitrarily reduced since an ideal filter can be approximated with arbitrary accuracy in the mean-square sense by a (noncausal) FIR filter (see, e.g., [8], p. 49). Indeed, problem (12) may become ill-posed for $\gamma=\infty$, if for fixed N, large values of μ and ν are required for obtaining a reasonable approximation. Well-posed solutions can be obtained by suitably choosing the "regularization" parameter γ [10], which imposes a certain degree of smoothness on the intersample magnitude of the approximating filter. Problem (12) can be easily recast in the framework of convex optimization and, more precisely, the solution can be efficiently derived by means of quadratic programming techniques. As a matter of fact, the objective function in Eq. (12) is a quadratic function of the impulse response samples h_k, while the class of filters $\mathscr{C}_{\mu\nu}^{\gamma}$ can be easily described by a set of linear constraints in the space of parameters h_k. In this paper the MATLAB® Optimization Toolbox® was used to solve such a problem.

The implementation of the noncausal pre-filter $\hat{Q}_{\mu\nu}$ requires that the reference signal be known with a preview of μ samples. If such an information is not available, a causal feedforward filter must be used choosing $\mu=0$. Alternatively, if the nominal filter $Q_{\mathrm{n}}(z)$ is stable, a causal approximation of the optimal filter can be given by $\hat{Q}_{\nu_c}=Q_{\mathrm{n}}(z)Q_{\Omega}(z)$ where $Q_{\Omega}(z)$ is a causal band-stop filter attenuating the frequency range $\Omega=\{\omega\in\Re\colon W_T(\omega)/|T_{\mathrm{n}}(\omega)|>1\}$.

4. A simulated example

In this section we illustrate the proposed procedure for the design of the feedforward filter through a numerical example. We consider a model set $\mathscr{M}_T$ given by Eq. (2) in which the nominal model is $T_{\mathrm{n}}(z)=(0.0175(z+1)^2)/(z^2-1.84z+0.91)$.

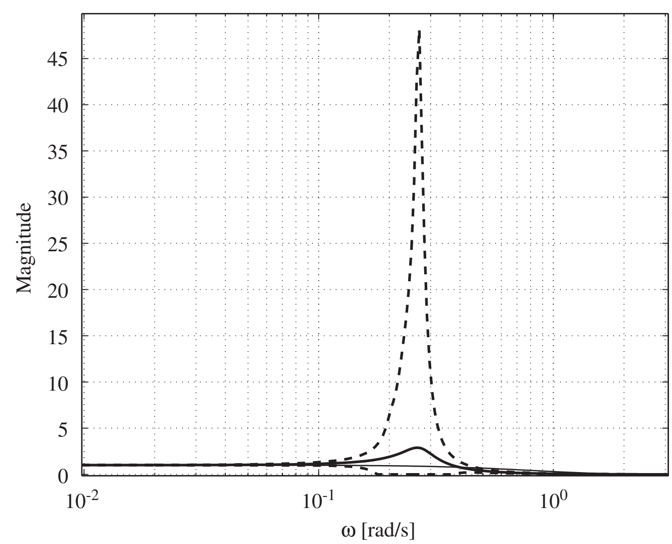

Fig. 5. Nominal closed loop $|T_{\mathrm{n}}|$ (solid), uncertainty bounds (dashed) and reference model $|M_{\mathrm{r}}|$ (thin).

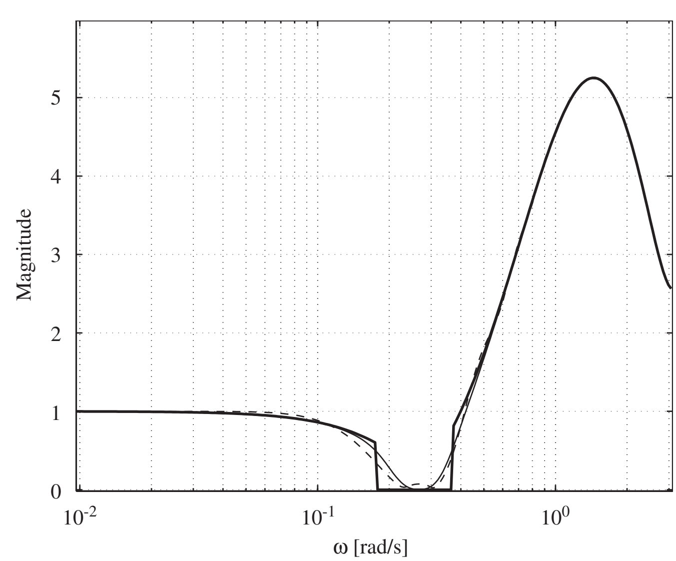

Fig. 6. Optimal filter $|Q^*|$ (solid), noncausal approximating FIR $|\hat{Q}_{\mu\nu}|$ (dashed) and causal approximating filter $|\hat{Q}_{\nu_c}|$ (thin).

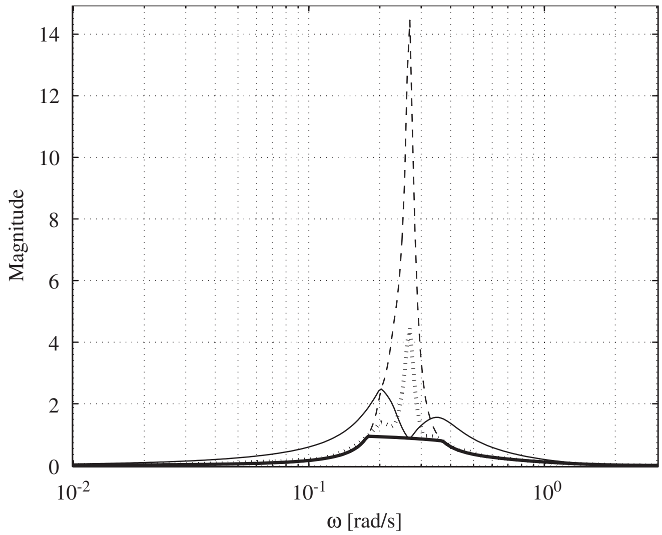

Fig. 7. Worst-case errors WME: optimal filter Q^* (solid), noncausal approximating FIR $\hat{Q}_{\mu\nu}$ (dotted), causal approximating filter $\hat{Q}_{\nu_c}$ (thin) and nominal filter Q_{n} (dashed).

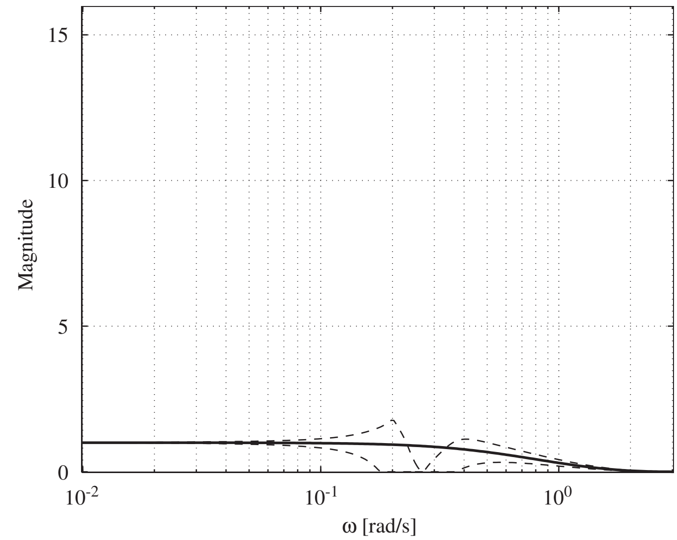

Fig. 9. Uncertainty bounds of $|\hat{Q}_{\nu_c}T|$ (dashed) and reference model $|M_{\mathrm{r}}|$ (solid).

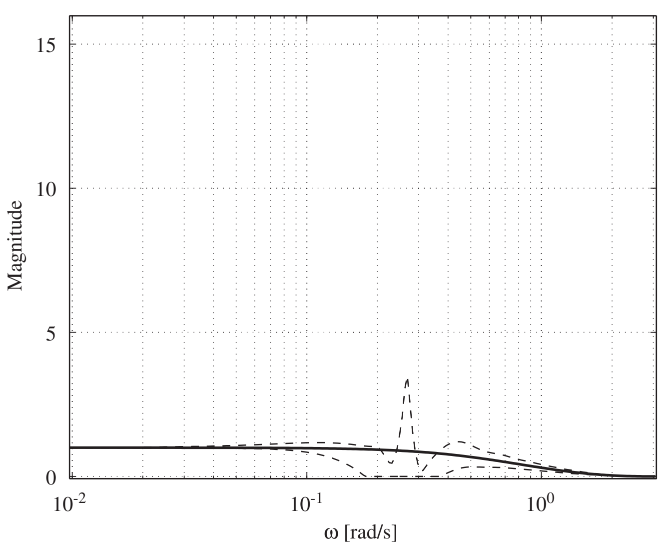

Fig. 8. Uncertainty bounds of $|\hat{Q}_{\mu\nu}T|$ (dashed) and reference model $|M_{\mathrm{r}}|$ (solid).

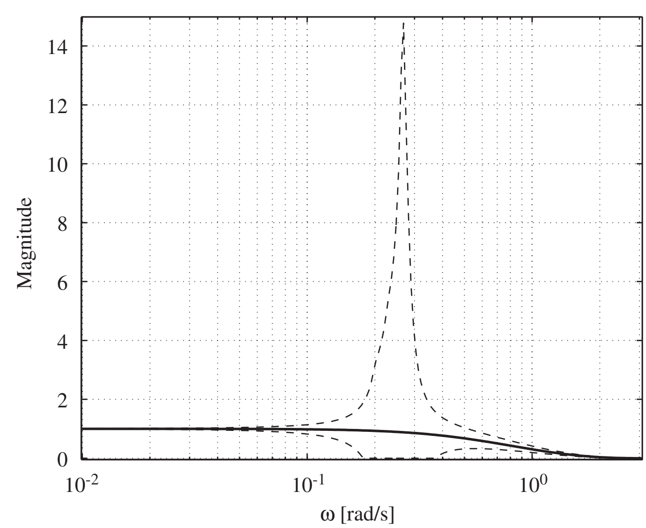

Fig. 10. Uncertainty bounds of $|Q_{\mathrm{n}}T|$ (dashed) and reference model $|M_{\mathrm{r}}|$ (solid).

The reference model $M_{\mathrm{r}} = (0.05194(z+1)^2(z+0.514))/((z-0.531)(z-0.2548)(z-0.1))$ was considered since it shows a desirable frequency response. The magnitudes $|M_{\mathrm{r}}(\omega)|$, $|T_{\mathrm{n}}(\omega)|$ and the uncertainty bounds are depicted in Fig. 5. In this example large uncertainty ($>100\%$) is present at middle frequencies; such a situation may arise, e.g., when both the natural frequency and the damping of a resonant system are affected by uncertainty. Fig. 6 shows the magnitude of the optimal filter $Q^*(\omega)$ (computed at 500 logarithmically spaced frequencies in the interval $[0, \pi]$), the magnitude of the noncausal filter $\hat{Q}_{\mu\nu}(\omega)$ (computed with $\mu = 30$, $\nu = 30$, W set to identity and $\gamma = \infty$), and the magnitude of the causal filter $\hat{Q}_{\nu_c} = Q_{\mathrm{n}}(z)Q_{\Omega}(z)$ of order 7th (where $Q_{\Omega}(z)$ is a bandstop digital Butterworth filter). Fig. 7 shows the worst-case matching error $\mathrm{WME}(\omega, Q)$ when the nominal filter $Q_{\mathrm{n}} = M_{\mathrm{r}}/T_{\mathrm{n}}$, the optimal filter Q^* and the two approximating filters $\hat{Q}_{\mu\nu}(\omega)$and $\hat{Q}_{\nu_c}$ are considered. The overall computation time required to compute filters $Q^*(\omega)$, $\hat{Q}_{\mu\nu}(\omega)$ and $\hat{Q}_{\nu_c}$ is about 0.6 s on a standard AMD Athlon® 2 GHZ laptop.

Note that in this example the value of γ has been set to ∞; under such an assumption (12) reduces to a standard unconstrained least-squares problem. However, even if $\gamma \neq \infty$ is chosen the problem is computationally tractable since the overall time required for the computation of $\hat{Q}_{\mu\nu}(\omega)$ is about 15 s. In order to highlight the effectiveness of the proposed approach, we present a comparison between the controlled system obtained with the designed filters $\hat{Q}_{\mu\nu}$, $\hat{Q}_{\nu_c}$ and the one obtained with Q_{n}. Figs. 8–10 show the uncertainty bounds on the frequency response of the transfer function from the reference to the output obtained with the filters $\hat{Q}_{\mu v}$, $\hat{Q}_{v_c}$ and Q_{n} respectively. From such figures it can be seen that, according to the result of Proposition 1, the designed filters provide a good matching of the frequency response of M_{r} through a considerable reduction of the uncertainty.

5. Conclusion

In this work we proposed a simple procedure for the design of the feedforward filter of a two degrees of freedom controller for uncertain SISO systems. Given an uncertainty model set for the complementary sensitivity function, the feedforward design problem has been formulated as a robust model matching problem. A closed form optimal solution is derived, which minimizes the worst-case model matching error at each frequency. We have shown that the optimal solution coincides with the filter obtained in the uncertainty free case over the frequency range where the complementary function uncertainty is less than 100%. On the contrary, it must be the null function at frequencies where the uncertainty is greater that 100%. Both causal and noncausal rational stable approximations of the optimal solution are obtained solving a quadratic programming problem. The effectiveness of the proposed approach has been shown by means of a simulated example.

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