# LMI Solution to Gain-constrained Robust Deadbeat Pole Assignment

# Hei Ka Tam James Lam\*

Department of Mechanical Engineering University of Hong Kong Pokfulam Road, HONG KONG

## Abstract

A novel optimization approach to robust deadbeat control is proposed. The design problem is cast into a convex programming task in which a special measure of closed-loop eigenvalue sensitivity is minimized. Advantages of the proposed method include: (1) Global optimality is guaranteed when the solution set is non-empty; (2) Constraints on the feedback gain can be catered naturally; (3) Minimum-gain deadbeat control design can be readily treated.

# 1. Introduction

Consider a linear time-invariant MIMO discrete time system

$$x_{t+1} = Ax_t + Bu_t$$
 ,  $t = 0, 1, 2, \dots$  (1)

where  $A \in \mathbb{R}^{n \times n}$ ,  $B \in \mathbb{R}^{n \times q}$ ,  $x_t \in \mathbb{R}^{n \times 1}$ ,  $u_t \in \mathbb{R}^{q \times 1}$ . Assume B is of full column rank while (A, B) is reachable with reachability indices  $k = k_1 \ge k_2 \ge \ldots \ge k_q$ . By applying a time-invariant state-feedback law

$$u_t = Kx_t \tag{2}$$

there results the closed-loop system given by

$$x_{t+1} = (A + BK)x_t \tag{3}$$

The reachability of (A,B) implies that the spectrum of the closed-loop state matrix  $M \triangleq A + BK$  can be assigned to any arbitrary set of self-conjugate complex numbers by proper choice of the feedback gain matrix  $K \in \mathbb{R}^{q \times n}$ . It is often desirable to assign the set of closed-loop poles at the origin of the complex plane. In such case, the closed-loop system exhibits deadbeat characteristics, with which zero-input response of the system dies down to zero in finite time steps. Furthermore, in order for a system under *Minimumtime Deadbeat Control (MTDC)*, that is, the regulation time to drive *every* initial state of the closed-loop system to the origin is made shortest, M is made similar to the block-diagonal matrix

$$J = \operatorname{diag}(J_1, J_2, \dots, J_q) \tag{4}$$

where  $J_p$  is a Jordan block of dimension  $k_p$  (for  $k_p = 0$ ,  $J_p$  does not appear in J).

By observing that M is nilpotent with order of nilpotence equals k ( $M^k=0$ ) and generally has a nontrivial Jordan structure, it is especially susceptible to spectral variation as a result of perturbation. As the feedback gain to achieve pole assignment for multi-input systems is in general non-unique, it is particularly meaningful for the non-uniqueness to be exploited in searching for a more robust eigenstructure.

# 2. Affine Parametrization of MTDC Feedback Gain

The idea of explicitly parametrizing the class of deadbeat regulators proposed by Funahashi et al. [2] is borrowed. Initially, (A, B) is transformed via  $S \in \mathbb{R}^{n \times n}$  into the Luenberger canonical form

$$y_{t+1} = SAS^{-1}y_t + SBu_t \qquad , \qquad y_t = Sx_t \qquad (5)$$

where

$$SAS^{-1} = J + E\hat{A} \qquad , \qquad SB = E\hat{B} \qquad (6)$$

in which

$$E = \operatorname{block} \operatorname{diag}(\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_q) \in \mathbb{R}^{n \times q}$$

$$\mathbf{e}_i = (0 \dots 0 1)^T \in \mathbb{R}^{k_i \times 1}$$

 $\hat{A} \in \mathbb{R}^{q \times n}$  and  $\hat{B} \in \mathbb{R}^{q \times q}$  are determined uniquely by (A, B). The transformation (6) results in the closed-loop state matrix being transformed into

$$S(A + BK)S^{-1} = J + E\hat{K}$$

where

$$\hat{K} = \hat{A} + \hat{B}KS^{-1} \in \mathbb{R}^{q \times n} \tag{7}$$

From Funahashi et al. [2] , it is not difficult to observe that  $\hat{K}$  can be expressed as

$$\hat{K} = \sum_{r=2}^{q} \sum_{s=1}^{r-1} \sum_{v=k_r+1}^{k_s} \gamma_{r,v+\sigma(s)} G_{r,v+\sigma(s)}$$
 (8)

where  $\sigma(s) = \sum_{p=1}^{s-1} k_p$  in which  $G_{r,v+\sigma(s)}$  denotes a matrix in  $\mathbb{R}^{q \times n}$  whose elements equal zero except the  $(r, v + \sigma(s))$  element equal to one. It follows from (7) and (8) that

$$K(\mathbf{w}) = K_0 + \sum_{i=1}^{N} w_i K_i$$
 ,  $\mathbf{w} = (w_1 \dots w_N)^T$  (9)

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where

$$\begin{array}{rcl} K_0 & = & -(\hat{B})^{-1}\hat{A}S \\ K_i & = & (\hat{B})^{-1}G_{r,v+\sigma(s)}S \quad , \quad w_i = \gamma_{r,v+\sigma(s)}(10) \\ \text{with the indices } r, \, s, \, v, \, \text{and } i \text{ being related by} \end{array}$$

$$i = \sum_{j=2}^{r-1} \sum_{l=1}^{j-1} (k_l - k_j) + (v + \sigma(s)) - sk_r$$
 (11)

 $N = nq - \sum_{p=1}^{q} (2p-1)k_p$  is the minimum number of independent free parameters  $w_i$  in parametrizing K.

#### Measure of Robustness 3.

Recently, Lam et al. [3] have shown that the spectral norm of M serves as a special measure of eigenvalue sensitivity for deadbeat control systems. In the following,  $||M||_2$  and  $||M||_{\text{max}}$  denotes respectively the spectral norm and the maximum norm of M ( maximum absolute value of the entries in M ).

**Theorem 1** Suppose M is subjected to a perturbation  $\Delta$  where  $\lambda$  is an eigenvalue of  $M + \Delta$ , then we have: (I)

$$\begin{aligned} |\lambda| &\leq & \max_{i=0,\dots,k-1} \{ (k||M^{i}\Delta||_{2})^{\frac{1}{i+1}} \} , \\ |\lambda| &\leq & \max_{i=0,\dots,k-1} \{ (k||M^{i}||_{2}||\Delta||_{2})^{\frac{1}{i+1}} \} , \\ |\lambda| &\leq & \max_{i=0,\dots,k-1} \{ (k||M||_{2}^{i}||\Delta||_{2})^{\frac{1}{i+1}} \} ; \end{aligned} (12$$

and (II)

$$\begin{aligned} |\lambda| &\leq (1+\epsilon)||M^{k-1}||_2^{\frac{1}{k}}||\Delta||_2^{\frac{1}{k}} \leq (1+\epsilon)||M||_2^{\frac{k-1}{k}}||\Delta||_2^{\frac{1}{k}} \\ where & \epsilon = \mathcal{O}(|\lambda|) \to 0 \text{ as } ||\Delta||_2 \to 0. \end{aligned} \tag{13}$$

It turns out that variations on the perturbed closedloop eigenvalues would be small if  $||M||_2$  is minimized.

### 4. Robust Pole Assignment

The Gain-constrained Robust Deadbeat Pole Assignment (GCRDPA) problem is now formulated as finding a state feedback gain K of constrained size to assign the set of closed-loop poles into the origin of the z-plane and at the same time minimize the sensitivity of the closed-loop zero eigenvalues. The problem is cast into a constrained minimization task:

$$\underset{\mathbf{w} \in \mathcal{P} \cap \mathcal{O}}{\text{minimize}} \ \phi(\mathbf{w}) = ||A + BK(\mathbf{w})||_2$$
 (14)

where

$$\mathcal{P} \triangleq \{ \mathbf{w} \mid ||K(\mathbf{w})||_2 < \alpha \} \tag{15}$$

and

$$Q \triangleq \{\mathbf{w} \mid ||K(\mathbf{w})||_{\max} < \beta\}$$
 (16)  
Since  $\phi(\mathbf{w})$  together with  $\mathcal{P}$ ,  $\mathcal{Q}$ , and  $\mathcal{P} \cap \mathcal{Q}$  are all convex in  $\mathbf{w}$ . (14) can be readily solved by state of

Since  $\phi(\mathbf{w})$  together with  $\mathcal{P}$ ,  $\mathcal{Q}$ , and  $\mathcal{P} \cap \mathcal{Q}$  are all convex in w, (14) can be readily solved by state-ofthe-art convex optimization routines. Moreover, (14) can be recast into a Semidefinite Programming (SDP) task in which a functional z is minimized subject to a set of Linear Matrix Inequality (LMI) constraints [1]:

$$minimize z$$
(17)

subject to

$$\begin{pmatrix} zI_n & M(\mathbf{w}) \\ M(\mathbf{w})^T & zI_n \end{pmatrix} > 0, \tag{18}$$

$$\begin{pmatrix} \alpha I_q & K(\mathbf{w}) \\ K(\mathbf{w})^T & \alpha I_n \end{pmatrix} > 0, \tag{19}$$

and

$$-\beta \boldsymbol{\zeta} < \mathbf{h} + F\mathbf{w} < \beta \boldsymbol{\zeta} \tag{20}$$

where

 $F = (\operatorname{vec}(K_1) \operatorname{vec}(K_2) \cdots \operatorname{vec}(K_N)) \in \mathbb{R}^{(q \times n) \times N},$  $\mathbf{h} = \text{vec}(K_0) \in \mathbb{R}^{(q \times n) \times 1}, \ \boldsymbol{\zeta} = (1 \dots 1)^T \in \mathbb{R}^{(q \times n) \times 1},$ and vec(.) denotes the lexicographical ordering of the elements of a matrix. Notice that (20) is a pair of polyhedron constraints which can be represented as

$$\operatorname{diag}(\beta \boldsymbol{\zeta} - \mathbf{h} - F\mathbf{w}) > 0 \tag{21}$$

and

$$\operatorname{diag}(\beta \boldsymbol{\zeta} + \mathbf{h} + F\mathbf{w}) > 0 \tag{22}$$

It turns out that if (18), (19), and (20) are feasible ( i.e.  $\mathcal{P} \cap \mathcal{Q} \neq \emptyset$ ), the solution produced by (17) will be globally optimal.

Remark 1 In (15) and (16), the greatest lower bound for  $\alpha$  and  $\beta$  to achieve deadbeat pole assignment can be computed using the following SDP settings.

To determine  $\inf_{\mathbf{w}} \alpha$ :

$$\begin{array}{ll}
\text{minimize } \alpha \\
\end{array} (23)$$

subject to

$$\begin{pmatrix} \alpha I_q & K(\mathbf{w}) \\ K(\mathbf{w})^T & \alpha I_n \end{pmatrix} > 0 \tag{24}$$

To determine  $\inf_{\mathbf{w}} \beta$ :

$$\begin{array}{ccc}
\text{minimize } \beta & (25)
\end{array}$$

subject to

$$\operatorname{diag}(\beta \zeta - \mathbf{h} - F\mathbf{w}) > 0 \tag{26}$$

and

$$\operatorname{diag}(\beta \boldsymbol{\zeta} + \mathbf{h} + F\mathbf{w}) > 0 \tag{27}$$

Notice that (23) and (25) by themselves serve as computational procedures for solving the Minimum-gain Deadbeat Pole Assignment (MGDPA) problem.

## References

- [1] S. Boyd, L. E. Ghaoui, E. Feron, and V. Balakrishnan. Linear Matrix Inequalities in System and Control Theory, volume 15. SIAM Studies in Applied Mathematics, 1994.
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