I. INTRODUCTION

Anti-windup is a traditional approach to dealing with actuator saturation. The idea is to augment the closed-loop system that was designed without taking actuator saturation into consideration so that the negative effect of actuator saturation is weakened. Earlier works on anti-windup design try to minimize the effect of saturation in a direct way by reducing the difference between the input and output of the actuators (see, for example, [1], [8]).

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A Switching Anti-windup Design Using Multiple Lyapunov Functions

Abstract—This technical note proposes a switching anti-windup design, which aims to enlarge the domain of attraction of the closed-loop system. Multiple anti-windup gains along with an index function that orchestrates the switching among these anti-windup gains are designed based on the min function of multiple quadratic Lyapunov functions. In comparison with the design of a single anti-windup gain which maximizes a contractively invariant level set of a single quadratic Lyapunov function as a way to enlarge the domain of attraction, the use of multiple Lyapunov functions and switching in the proposed design allows the union of the level sets of the multiple Lyapunov functions, each of which is not necessarily contractively invariant, to be contractively invariant and within the domain of attraction. As a result, the resulting domain of attraction is expected to be significantly larger than the one resulting from a single anti-windup gain and a single Lyapunov function. Indeed, simulation results demonstrate such a significant improvement.

Index Terms—Actuator saturation, anti-windup, composite Lyapunov functions, domain of attraction, switching systems.

REFERENCES

to maximize the contractively invariant ellipsoid is then formulated as a constrained optimization problem with bilinear matrix inequalities. An iterative LMI algorithm is developed to solve this optimization problem. Numerical examples demonstrate that such a design procedure is indeed effective in achieving a large domain of attraction.

On the other hand, switching systems have been extensively studied in recent years. A large portion of the literature has focused on the stability analysis and controller design of switched systems (see, for example, [2], [5], [6], [13], [19], [23], [26] and the references therein). By employing either common or multiple Lyapunov functions, switching strategies are developed to make the resulting switched systems asymptotically stable. In a recent paper [13], three methods for composing a Lyapunov function from a group of quadratic functions for stabilization of switched systems composed of a number of linear systems are examined in detail. The resulting Lyapunov functions are referred to as the min function, the max function, and the convex hull function. In particular, the min function is defined at each state as the minimum value among all the quadratic functions in the group. Unlike the max and convex hull functions, both of which are convex, the min function is not a convex function and its level set is the union of the level sets of the individual quadratic functions. However, as explained in [13], the min function is more convenient to use in the synthesis of switched control systems.

There has also been effort on the design of switched systems in the presence of actuator saturation. For example, the idea of switching has been applied to a family of linear systems in the presence of actuator saturation with the objectives of enlarging the domain of attraction [20] and tolerating/rejecting disturbances [21].

In this technical note, we explore the idea of switching among multiple anti-windup gains in order to further enlarge the domain of attraction of the resulting control systems. In particular, we will revisit the anti-windup design problem considered in [3], in which an algorithm is proposed to design a single anti-windup gain that enlarges the domain of attraction of the closed-loop system, which is estimated as a contractively invariant ellipsoid, a level set of a quadratic Lyapunov function. Here in this technical note we will use the min function approach developed in [13] to design multiple anti-windup gains and a switching strategy to further enlarge the domain of attraction beyond what can be achieved by the single anti-windup gain of [3]. The union of several ellipsoids, as the level set of the min function, is expected to help enlarge the domain of attraction. More significantly, thanks to switching, each of these individual ellipsoids is not required to be contractively invariant for their union to be contractively invariant. Thus, each of these individual ellipsoids is expected to be larger than the contractively invariant ellipsoid resulting from the single Lyapunov function design approach of [3].

The remainder of the technical note is organized as follows. In Section II, we state the problem to be studied in this technical note. Section III summarizes some tools that we will use to solve the problem. Section IV presents the algorithm for constructing anti-windup gains and a switching strategy that governs them. Numerical examples are presented in Section V to demonstrate the effectiveness of the anti-windup design approach proposed in Section IV. Section VI concludes the technical note.

II. PROBLEM FORMULATION

Consider a linear system subject to actuator saturation

\[
\begin{align*}
\dot{x} &= Ax + B \text{sat}(u), \\
y &= Cx,
\end{align*}
\]

where \( x \in \mathbb{R}^n \) is the state, \( u \in \mathbb{R}^m \) is the control input, \( y \in \mathbb{R}^p \) the measured output, the function \( \text{sat} : \mathbb{R}^m \to \mathbb{R}^m \) is the vector valued standard saturation function defined as

\[
\text{sat}(u) = \begin{bmatrix} \text{sat}(u_1) & \text{sat}(u_2) & \cdots & \text{sat}(u_m) \end{bmatrix}^T, \quad \text{sat}(u_i) = \text{sign}(u_i) \min\{ |u_i|, 1 \}.
\]

We have slightly abused the notation by using \( \text{sat} \) to denote both the scalar valued and the vector valued saturation functions. Also note that it is without loss of generality to assume unity saturation level. A nonunity saturation level can be absorbed into the \( B \) matrix and the feedback gain.

We assume that a linear dynamic controller of the form

\[
\begin{align*}
\dot{x}_c &= Ax_c + B_cy, \\
y &= C_c x_c + D_cy,
\end{align*}
\]

has been designed that stabilizes the system (1) with desired performances in the absence of actuator saturation. When the actuator saturates, control input delivered to the system \( \text{sat}(u) \) is different from the designed control input \( u \), causing the performance of the closed-loop systems, for example, the size of the stability region and the transient response, to degrade. To alleviate this degradation, an anti-windup compensator is designed that modifies the controller with a “correction” term \( E_c (\text{sat}(u) - u) \) as follows:

\[
\begin{align*}
\dot{x}_c &= Ax_c + B_cy + E_c (\text{sat}(u) - u), \\
y &= C_c x_c + D_cy.
\end{align*}
\]

Under this compensated controller, the closed-loop system can be written as

\[
\begin{align*}
\dot{x} &= \tilde{A} \dot{x} + \tilde{B} (\text{sat}(u) - u), \\
y &= F \tilde{x},
\end{align*}
\]

where \( \tilde{x} = [x^T \ x_c^T]^T \) and

\[
\begin{align*}
\tilde{A} &= \begin{bmatrix} A + B D_c C & B C_c \end{bmatrix}, \\
\tilde{B} &= \begin{bmatrix} B \\ E_c \end{bmatrix}, \\
F &= \begin{bmatrix} D_c C_c \\ C_c \end{bmatrix}.
\end{align*}
\]

In [3], an algorithm was developed based on the use of a single quadratic Lyapunov function to design the anti-windup gain matrix \( E_c \) that enlarges the domain of attraction of the resulting closed-loop system (2). In this technical note, we will develop a new algorithm based on multiple Lyapunov functions to design several anti-windup gains \( E_{ci}, i \in I \{1, N\} \), and a switching strategy \( i = \sigma(\tilde{x}) \) to govern these anti-windup gains so that the domain of attraction of the resulting closed-loop system is further enlarged. Here and throughout the technical note, for two integers \( k_1 \) and \( k_2, I \{k_1, k_2\} \) denotes the set of integers \( \{k_1, k_1 + 1, \ldots, k_2\} \). The function \( \sigma(\tilde{x}) \) determines which system is in operation according to the value of the state \( x \) and takes the form of \( \sigma(\tilde{x}) = i \) for \( \tilde{x} \in \Omega_i, \) with \( \cup_{i=0}^{N} \Omega_i = \mathbb{R}^{n+mc} \). Consequently, the resulting closed-loop system can be written as

\[
\begin{align*}
\dot{x} &= \tilde{A} \dot{x} + \tilde{B}_i (\text{sat}(u) - u), \\
y &= F \tilde{x},
\end{align*}
\]

where \( \tilde{A} \) and \( F \) are as defined above and

\[
\tilde{B}_i = \begin{bmatrix} B \\ E_{ci} \end{bmatrix}.
\]

III. PRELIMINARIES

Given positive definite matrices \( P_j \in \mathbb{R}^{m \times m}, j \in I \{1, J\} \), the min function can be defined as follows:

\[
V_{\min}(x) = \min \{ x^T P_j x : j \in I \{1, J\} \}
\]

Denote the 1-level set of \( V_{\min} \) as \( L_{V_{\min}} = \{ x \in \mathbb{R}^n : V_{\min}(x) \leq 1 \} \). Then we have \( L_{V_{\min}} = \cup_{j=1}^{J} E(P_j) \), where

\[
E(P_j) = \{ x \in \mathbb{R}^n : x^T P_j x \leq 1 \}.
\]

Since \( V_{\min} \) is not differentiable everywhere, it is necessary to analyze the directional derivatives of \( V_{\min} \), which characterize the be-
When sliding motions occur in a switched system, its trajectories move along the switching surface according to Filippov's convex combination [7], \( \dot{x} = \sum_{i \in \mathbb{I}_{m}} \alpha_i A_i x, \) with \( \alpha_i \geq 0 \) and \( \sum_{i \in \mathbb{I}_{m}} \alpha_i = 1. \) Here \( \mathbb{I}_{m} \) is the set of indices of all subsystems involved in the sliding motion. For the switched system (4), the derivatives of \( V_{\min} \) in the sliding mode are characterized as follows.

**Proposition 1 ([13]):** Consider a sliding mode involving subsystems \( \dot{x} = A_i x, \ i \in \mathbb{I}_{m}. \) Then for each \( x \) in this sliding mode

\[
V_{\min}(x, A_i x) = \mu(x). \quad \forall i \in \mathbb{I}_{m}. \]

Moreover, along the sliding direction \( \Sigma_{i \in \mathbb{I}_{m}} \alpha_i A_i x, \) where \( \alpha_i \geq 0 \) and \( \sum_{i \in \mathbb{I}_{m}} \alpha_i = 1, \)

\[
V_{\min}(x_0, \Sigma_{i \in \mathbb{I}_{m}} \alpha_i A_i x_0) = \mu(x_0). \]

In this technical note, we consider the switched system (3), which results from a system under a saturated linear feedback and a switched anti-windup compensator. We recall a tool from [12] for expressing a saturated linear feedback anti-windup compensator. We recall a tool from [12] for expressing a saturated linear feedback anti-windup compensator.

**IV. A SWITCHING ANTI-WINDUP COMPENSATOR**

Consider the switched system (3), we will use the min function composed from \( J \) quadratic functions \( V_j(\dot{x}) = \dot{x}^T P_j \dot{x}, \) \( V_{\min}(\dot{x}) = \min \{ \dot{x}^T P_j \dot{x} : j \in \mathbb{I}_{m}, \} \), and the switching law that results from

\[
\sigma(\dot{x}) = \arg \min_{i \in \mathbb{I}_{m}} V_{\min}(\dot{x} : (A_i - \bar{B}_i) \dot{x} + \bar{B}_i \text{sat}(F \dot{x})). \quad (5)
\]

When \( \sigma(\dot{x}) \) is multi-valued, any of the values can be chosen. In our simulation, we choose the value in such a way that switching from the \( i \)-th anti-windup gain at a state \( \dot{x} \) occurs only when \( i \notin \sigma(\dot{x}) \). Let

\[
\mu(\dot{x}) = \min_{i \in \mathbb{I}_{m}} V_{\min}(\dot{x} : (A_i - \bar{B}_i) \dot{x} + \bar{B}_i \text{sat}(F \dot{x})). \quad (6)
\]

Then, the behavior of the system in a sliding mode is characterized by the following proposition, which is a slight generalization of Proposition 1.

**Proposition 2:** Consider a set of subsystems \( \dot{x} = (A_i - \bar{B}_i) \dot{x} + \bar{B}_i \text{sat}(F \dot{x}), i \in \mathbb{I}_{m}, \) that are involved in a sliding mode. Then

\[
V_{\min}(x_0, (A_i - \bar{B}_i) \dot{x}_0 + \bar{B}_i \text{sat}(F \dot{x}_0)) = \mu(x_0), \quad \forall i \in \mathbb{I}_{m}. \quad (7)
\]

Moreover, we have

\[
V_{\min}(x_0, \Sigma_{i \in \mathbb{I}_{m}} \alpha_i ((A_i - \bar{B}_i) \dot{x}_0 + \bar{B}_i \text{sat}(F \dot{x}_0))) = \mu(x_0). \quad (8)
\]

where \( \alpha_i \geq 0 \) and \( \sum_{i \in \mathbb{I}_{m}} \alpha_i = 1. \)

**Remark 1:** Proposition 2 indicates that, if \( P_j, j \in \mathbb{I}_{[1, J]}, \) can be chosen such that \( \mu(\dot{x}) < 0, \) for all \( \dot{x} \in L_{\mathbb{I}_{m}} \setminus \{0\}, \) system (3) is asymptotically stable at the origin with \( L_{\mathbb{I}_{m}} = \cup_{j \in \mathbb{I}_{J}} \mathcal{E}(P_j) \) contained in the domain of attraction, in disregard of the existence of the sliding motion. Theorem 1 below characterizes such matrices \( P_j. \)

**Theorem 1:** Given \( P_j > 0, \ j \in \mathbb{I}_{[1, J]}, \) if there exist matrices \( H_{ij} \in \mathbb{R}^{n \times n}, \alpha_{ij} \geq 0 \) and \( \delta_{ij} \geq 0, i \in \mathbb{I}_{[1, N]}, j \in \mathbb{I}_{[1, J]}, \) such that

\[
(\Sigma_{i \in \mathbb{I}_{m}} \alpha_{ij} (A_i - \bar{B}_i) \dot{x} + \bar{B}_i (E_i F + E_i H_{ij}) \dot{x})^T \dot{P}_j + \dot{P}_j (\Sigma_{i \in \mathbb{I}_{m}} \alpha_{ij} (A_i - \bar{B}_i) \dot{x} + \bar{B}_i (E_i F + E_i H_{ij})) < 0, \quad \forall s \in [1, 2m], j \in [1, J]. \quad (8)
\]

and \( \mathcal{E}(P_j) \subset \mathcal{L}(H_{ij}), i \in [1, N], j \in [1, J], \) then the system (3) with the switched anti-windup compensator as governed by the switching law (5) is asymptotically stable at the origin with \( \cup_{j \in \mathbb{I}_{J}} \mathcal{E}(P_j) \) contained in the domain of attraction.

**Proof:** In view of Remark 1, we need only to show that \( \mu(\dot{x}) < 0 \) for all \( \dot{x} \in \left( \cup_{j \in \mathbb{I}_{J}} \mathcal{E}(P_j) \right) \setminus \{0\}. \) For any \( \dot{x} \in \left( \cup_{j \in \mathbb{I}_{J}} \mathcal{E}(P_j) \right) \setminus \{0\}, \) by definition of \( J_{\min}(\dot{x}), \dot{x} \in \mathcal{E}(P_j) \subset \mathcal{L}(H_j), \forall i \in [1, N], j \in J_{\min}(\dot{x}). \) Thus, it follows from Lemma 2 that

\[
\text{sat}(F \dot{x}) \in \{ E_i F \dot{x} + E_i H_{ij} \dot{x}, \ s \in [1, 2m] \} \quad \forall i \in [1, N], j \in J_{\min}(\dot{x})
\]

and that

\[
(A_i - \bar{B}_i) \dot{x} + \bar{B}_i \text{sat}(F \dot{x}) \in \{ (A_i - \bar{B}_i) \dot{x} + \bar{B}_i (E_i F + E_i H_{ij}) \dot{x}, \ s \in [1, 2m] \} \quad \forall i \in [1, N], j \in J_{\min}(\dot{x}). \quad (9)
\]
Also by the definition of $J_{\min}(\tilde{x})$, we have $\tilde{x}^T (P_j - P_k) \tilde{x} \leq 0, \forall k \in I[1, J]$, $j \in J_{\min}(\tilde{x})$. It thus follows from (8) that

$$2 \tilde{x}^T P_j (\sum_{i=1}^N \alpha_{ij} (\tilde{A} - \tilde{B}_i F + \tilde{B}_i (E_i F + E_i^T H_{ij}))) \tilde{x} < 0$$

$$s \in I[1, 2^m], \ j \in J_{\min}(\tilde{x}).$$

(10)

Since $\alpha_{ij} \geq 0$ and $\sum_{i=1}^N \alpha_{ij} = 1$ for each $j$, it follows that:

$$\min \{2 \tilde{x}^T P_j (\tilde{A} - \tilde{B}_i F + \tilde{B}_i (E_i F + E_i^T H_{ij}))) \tilde{x}:$$

$$i \in I[1, N] \} < 0, \quad s \in I[1, 2^m], \ j \in J_{\min}(\tilde{x}).$$

(11)

Recalling definition (6) of $\mu(\tilde{x})$, and in view of Lemma 1, (9), and (11), we have

$$\mu(\tilde{x}) := \min \{V_{\min}(\tilde{x})): (\tilde{A} - \tilde{B}_i F) \tilde{x} + \tilde{B}_i (F \tilde{x}) : i \in I[1, N] \} = \min \{2 \tilde{x}^T P_j ((\tilde{A} - \tilde{B}_i F) \tilde{x} + \tilde{B}_i (F \tilde{x})):$$

$$i \in I[1, N] \} \leq \max_{s \in I[1,2^m]} \min_{\mu(\tilde{x})} \{2 \tilde{x}^T P_j (\tilde{A} - \tilde{B}_i F + \tilde{B}_i (E_i F + E_i^T H_{ij}))) \tilde{x}: i \in I[1, N] \} < 0.$$ 

This completes the proof.

With Theorem 1, our design objective boils down to obtaining $E_{ci}, i \in I[1, N]$, and $P_j > 0, j \in I[1, J]$, such that $\cup_{j=1}^J \mathcal{E}(P_j)$ is maximized. This can be achieved by maximizing the individual $\mathcal{E}(P_j)$. We will achieve the latter by maximizing the scalar $\alpha$ such that $\alpha \gamma_{ij} \in \mathcal{E}(P_j), i \in I[1, J]$, where $r_j \in \mathbb{R}^n$ are some given vectors. Consequently, our design can be cast into the following optimization problem:

$$\sup_{\gamma_{ij}, E_{ci}, H_{ij}, \alpha_{ij}, \beta_{jk}}$$

$$\alpha$$

s.t. (a) $\alpha_{ij} \in \mathcal{E}(P_j)$, $j \in I[1, J]$, (b) Inequalities (8), (c) $\mathcal{E}(P_j) \subseteq \mathcal{L}(H_{ij}), i \in I[1, N], j \in I[1, J]$, (d) $P_j > 0, \beta_{jk} > 0, \alpha_{ij} > 0, \sum_{i=1}^N \alpha_{ij} = 1, i \in I[1, N], j, k \in I[1, J]$. (12)

Constraint (a) is equivalent to $\alpha^2 r_j^T P_j r_j \leq 1$ or $1/\alpha^2 - r_j^T P_j r_j \geq 0$. Constraint (c) is equivalent to $h_{ij}, P_j^{-1} h_{ij}^T \leq 1$, or

$$\left[ \begin{array}{c} h_{ij}^T \ h_{ij} \end{array} \right] \geq 0,$$

where $h_{ij}$ is the $i$th row of $H_{ij}$.

Thus, letting $\nu = 1/\alpha^2$, we can rewrite the optimization problem (12) as the following BMI problem:

$$\inf_{r_j^T P_j r_j \leq \nu, j \in I[1, J]}$$

s.t. (a) $r_j^T P_j r_j \leq \nu$, $j \in I[1, J]$, (b) Inequalities (8), (c) $\left[ \begin{array}{c} h_{ij}^T \ h_{ij} \end{array} \right] \geq 0, i \in I[1, m], i \in I[1, N], j \in I[1, J]$. (d) $P_j > 0, \beta_{jk} > 0, \alpha_{ij} > 0, \sum_{i=1}^N \alpha_{ij} = 1, i \in I[1, N], j, k \in I[1, J]$. (13)

BMI problems are non-convex optimization problems. But we can obtain local optimal solutions by fixing a group of parameters and optimize over the remaining ones. In particular, in this technical note, we will, for simplicity, set $J = N$ and $H_{ij} = H_j$. We will use the iterative algorithm in [3] to determine the variables $E_{ci}$ and $H_j$ first, and then, with $E_{ci}$ and $H_j$ fixed, search for the remaining parameters $\beta_{jk}, \alpha_{ij}$ and $P_j$. The essence of the iterative algorithm of [3] is the following. Denote

$$P_j = \left[ \begin{array}{c} P_j(1, 1) \ P_j(1, 2) \end{array} \right] \begin{array}{c} P_j(2, 1) \ P_j(2, 2) \end{array}, \quad \hat{B}_0 = \left[ \begin{array}{c} B \ 0 \end{array} \right].$$

(14)

where $P_j(1, 1) \in \mathbb{R}^{n \times n}, P_j(1, 2) \in \mathbb{R}^{n \times n}$ and $P_j(2, 2) \in \mathbb{R}^{n \times n}$. Then, $P_j \hat{B}_j = P_j \hat{B}_0 + P_j \hat{E}_{ci}$. By setting $\beta_{jk} = 0$, the nonlinear matrix inequalities (8) can be written as

$$A^T P_j + P_j A + ((E_i F + E_i^T H_j) - F)^T (P_j \hat{B}_0 + P_j \hat{E}_{ci})^T + (P_j \hat{B}_j + P_j \hat{E}_{ci})(E_i F + E_i^T H_j) - F \leq 0.$$ (15)

If we fix the values of $P_j(1, 2), P_j(2, 2)$ and $H_j$, the inequalities (15) are LMIs in $P_j(1, 1)$ and $H_j$. Thus, we can determine $E_{ci}$ such that $P_j(1, 1)$ is as “small” as possible, making the region $\{x \in \mathbb{R}^n: x^T P_j(1, 1) x \leq 1\}$ as large as possible.

We will summarize our approach to solving the optimization problem (13) in the following algorithm.

**Design Algorithm for a Switched Anti-Windup Compensator:**

**Step 1:** Set $j = 1$.

**Step 2:** Set a reference vector $r_j$ and $E_{ci} = 0$, solve the optimization problem that is derived in [3]:

$$\inf_{P_j(1, 1) > 0, E_{ci}} \nu_j,$$

s.t. (a) $r_j^T P_j r_j \leq \nu_j,$ (b) $Q_j (\tilde{A} - \tilde{B}_i F)^T + (\tilde{A} - \tilde{B}_i F) Q_j + (E_i F, Q_j + E_i^T G_j)^T \tilde{B}_j + (E_i F, Q_j + E_i^T G_j) \leq 0,$

$$s \in I[1, 2^m].$$ (16)

where $Q_j = P_j^{-1}, G_j = H_j Q_j$ and $g_{ij}$ is the $i$th row of $G_j$. Denote the solution as $r_{ij, 0}, Q_{ij, 0}, G_{ij, 0}$.

**Step 3:** Set $E_{ci}$ with an initial value, $q = 1$ and $r_{opt, ij} = 1$.

**Step 4:** Solve the optimization problem (16) for $r_{ij, q}, Q_{ij, q}$, and $G_{ij, q}$, respectively.

**Step 5:** Let $\nu_{opt, ij} = \nu_{ij, q} + \nu_{opt, ij}, \nu_j = \nu_{ij, q} + \nu_j, P_j = Q_j^{-1}$ and $H_j = G_j Q_j^{-1}$.

**Step 6:** If $|\nu_j - |1| > \delta$, a pre-determined tolerance, GOTO Step 7, ELSE GOTO Step 8.

**Step 7:** Solve the following LMI problem:

$$\inf_{P_j(1, 1) > 0, E_{ci}} \nu,$$

s.t. (a) $r_j^T P_j r_j \leq \nu$, (b) $A^T P_j + P_j A + ((E_i F + E_i^T H_j) - F)^T (P_j \hat{B}_0 + P_j \hat{E}_{ci})^T + (P_j \hat{B}_j + P_j \hat{E}_{ci})(E_i F + E_i^T H_j) - F \leq 0,$

$$s \in I[1, 2^m].$$ (17)

**Step 8:** If $\nu_{opt, ij} < 1$, then, $\alpha_{ij} = (\nu_{opt, ij})^{-1/2}$ and $E_{ci}$ is a feasible solution and GOTO Step 9, ELSE set $E_{ci}$ with another initial value and GOTO Step 3.

**Step 9:** If $j < J$, set $j = j + 1$, and GOTO Step 2, ELSE GOTO Step 10.
Step 10: With the obtained $E_2$ and $P_2(1, 1)$, $j \in I[1, J]$, and fixing $\alpha_{ci} = 1, i \in I[1, N]$, we can solve the problem (13) to obtain the largest $\mathcal{E}(P_j), j \in I[1, J]$, by sweeping over the parameters $\beta_{ji}$.

Remark 2: To prevent the anti-windup gain from being too high, we can constrain $E_{ci} = \{e_{ci}(p, q)\}_{p \in \mathbb{R}, q \in \mathbb{N}}$ element-by-element as follows:

$$\varphi_i(p, q) \leq e_{ci}(p, q) \leq \varphi_i(p, q), \quad p \in I[1, n_c], \quad q \in I[1, m]$$

which are linear and can be readily added to the optimization process.

V. A NUMERICAL EXAMPLE

Consider the benchmark example in ([3], [4]):

$$\dot{x}_1 = -0.1 x_1 + 0.5 \text{sat}(u_1) + 0.4 \text{sat}(u_2),$$

$$\dot{x}_2 = -0.1 x_2 + 0.4 \text{sat}(u_1) + 0.3 \text{sat}(u_2)$$

where $u_1$ and $u_2$ are constrained to $[-3, 3]$ and $[-10, 10]$, respectively. At time $t = 0$, the outputs $x_1$ and $x_2$ are subject to pulse set-point step changes with the duration of 20 seconds and the magnitudes of 2 and 1, respectively. The PI controller considered in ([3], [4]) is:

$$\dot{x}_{1,c} = y_{sp1} - x_1 + e_{11} (\text{sat}(u_1) - u_1) + e_{12} (\text{sat}(u_2) - u_2),$$

$$\dot{x}_{2,c} = y_{sp2} - x_2 + e_{21} (\text{sat}(u_1) - u_1) + e_{22} (\text{sat}(u_2) - u_2),$$

$$u_1 = 10(y_{sp1} - x_1) + x_{1,c},$$

$$u_2 = -10(y_{sp2} - x_2) - x_{2,c}$$

where $y_{sp1}$ and $y_{sp2}$ are the set point steps for outputs. In the absence of actuator saturation, the PI controller places the closed-loop system poles at $\{-1, -1, -0.1, -0.1\}$. To apply our algorithm, let us set

$$A = \begin{bmatrix} -0.1 & 0 \\ 0 & -0.1 \end{bmatrix},$$

$$B = \begin{bmatrix} 0.5 & 0.4 \\ 0.4 & 0.3 \end{bmatrix},$$

$$C = \begin{bmatrix} 1 \\ 0 \end{bmatrix},$$

$$D = \begin{bmatrix} 0.3333 \\ 0.3333 \end{bmatrix},$$

$$E = \begin{bmatrix} 3 \\ 0 \end{bmatrix}.$$
and the switching between the systems along the trajectory shown in Fig. 1.

Fig. 2: $V_{\text{min}}$ and the switching between the systems along the trajectory shown in Fig. 1.

Fig. 3: State responses with different anti-windup designs.

Fig. 4: Input signals with different anti-windup designs.

Fig. 5: Unstable open loop system: The union of the ellipsoids $E_1(P_1(1, 1), 1)$ and $E_2(P_2(1, 1), 1)$ and a state trajectory that starts from a point on the boundary of the union.

VI. CONCLUSION

This technical note revisited the problem of anti-windup compensator design and proposed an algorithm for designing a switched anti-windup compensator. A switched anti-windup compensator consists of a group of anti-windup gains and a switching law that governs the switching among these anti-windup gains. Our design is based on the min function defined from a group of quadratic Lyapunov functions. Such a min function was recently recognized to facilitate the design and analysis of switched systems composed of linear systems. Our simulation results indicate that the proposed switched anti-windup compensator has the ability to enlarge the domain of attraction of the resulting closed-loop system significantly beyond what a single anti-windup gain is able to achieve.

REFERENCES

A Weighted Least-Squares Approach to Parameter Estimation Problems Based on Binary Measurements

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Abstract—We present a new approach to parameter estimation problems based on binary measurements, motivated by the need to add integrated low-cost self-test features to microfabricated devices. This approach is based on the use of original weighted least-squares criteria: as opposed to other existing methods, it requires no dithering signal and it does not rely on an approximation of the quantizer. In this technical note, we focus on a simple choice for the weights and establish some asymptotic properties of the corresponding criterion. To achieve this, the assumption that the quantizer’s input is Gaussian and centered is made. In this context, we prove that the proposed criterion is locally convex and that it is possible to use a simple gradient descent to find a consistent estimate of the unknown system parameters, regardless of the presence of measurement noise at the quantizer’s input.

Index Terms—Binary sensors, FIR digital filters, parameter estimation, quantized observations.

I. INTRODUCTION

In this technical note, we present a new parameter estimation method based on binary measurements. This work was originally motivated by the need to add integrated low-cost self-test features to microfabricated devices, such as MEMS and NEMS. Even though there exists a wide range of applications where identification methods based on binary observations are necessary or desirable [1], the focus is brought here on the test of microelectronic devices. It is well-known that, as characteristic dimensions become smaller, the dispersions afflicting electronic devices tend to become larger. Typical sources of uncertainty and dispersion are variations in the fabrication process, changes in the operating conditions or imperfect knowledge of physics. As a consequence, it is usually impossible to guarantee a priori that a given device will function properly. Expensive tests must then be run after fabrication to ensure that only suitable devices are commercialized. Furthermore, self-test (and self-tuning) features, such as parameter estimation routines, must often be implemented, so that devices can adapt to changing conditions. However, most parameter estimation methods [2], [3] rely on high-resolution digital measurements. Their integration requires the implementation of high-resolution analog-to-digital converters (ADCs) and, thus, results in longer design times, larger silicon areas and increased costs. Our objective is then to develop a parameter estimation method that relies on very low-resolution (ideally binary) measurements, in order to keep the added cost of testing as small as possible.

In the field of micro-electronics, the issue of parameter estimation of linear systems from binary data has partially been addressed by Ngreiros [4] and Juillard and Colinet [5]. In [5], a white Bernoulli input...