

Computation of Feedback Control for Time Optimal State Transfer using Groebner Basis

Deepak Patil, Ameer Mulla, Debraj Chakraborty*, Harish Pillai

Department of Electrical Engineering, Indian Institute of Technology Bombay, Mumbai-400076

Abstract

Computation of time optimal feedback control law for a controllable linear time invariant system with bounded inputs is considered. Unlike a recent paper by the authors, the target final state is not limited to the origin of state-space, but is allowed to be in the set of constrained controllable states. Switching surfaces are formulated as semi-algebraic sets using Groebner basis based elimination theory. Using these semi-algebraic sets, a nested switching logic is synthesized to generate the time optimal feedback control. However, the optimal control law enforces an unavoidable limit cycle in the time-optimal trajectory, for most non-origin target points. The time-period of this limit-cycle is dependent on the target position. This dependence is algebraically characterized and a method to compute the time-period of the limit-cycle is provided. As a natural extension, the set of constrained controllable states is also computed.

1. Introduction

Recent advances in computer algebra packages have facilitated application of tools from algebraic geometry (in particular Groebner basis) to solve important problems in control theory (see [1, 2, 3]). In this work, we apply Groebner basis methods to the problem of computation of feedback control (from a constrained set $|u| \leq 1$) for the minimum time state-transfer of a linear time invariant (LTI) system. The Pontryagin's minimum principle (PMP) provides the open loop optimal solution, according to which,

*Corresponding author

Email addresses: deepakp@ee.iitb.ac.in (Deepak Patil), ameerkm@ee.iitb.ac.in (Ameer Mulla), dc@ee.iitb.ac.in (Debraj Chakraborty), hp@ee.iitb.ac.in (Harish Pillai)

Preprint submitted to System and control letters

February 17, 2015

13 the input switches between extreme admissible values ± 1 [4]. The feedback solution,
14 however, requires knowledge of the so called *switching surfaces* in the state-space. If the
15 equations for the switching surfaces (in terms of the state variables) can be computed,
16 then it is possible to synthesize the optimal feedback using the sign of the current state
17 with respect to switching surface. A partial solution to this synthesis problem was
18 provided in [5] for a class of systems with positive eigenvalues and later on extended to
19 non-zero distinct rational eigenvalues in [6]. In these papers, a time optimal feedback
20 control law was synthesized (using Groebner basis) which transfers admissible initial
21 states to the *origin* and keeps the state-trajectory arbitrarily close to the origin. In this
22 article, we consider a class of systems with distinct and rational eigenvalues and extend
23 our earlier results from [5, 6] for minimum time state transfer to *non-origin* target points.

24 Optimal feedback is preferred over open loop solutions for robustness to disturbances
25 as well as reduction in real time computational load. Time optimal feedback control has
26 been employed, among others, in space-craft attitude control [7], robotic manipulators [8],
27 pursuit evasion games [9] and multi-agent consensus tracking [10]. Control to non-origin
28 targets is desirable when linearized equations of the corresponding non-linear system are
29 valid over a wide range of operating conditions and tracking of different set points (not
30 necessarily the equilibrium point) may be needed. Such situations occur regularly in a
31 variety of applications (e.g. see [11] and references therein). The analytical foundations
32 for the switching surfaces in time optimal control was laid out in [12, 13] and later
33 extended for non-origin target points in [14, 15, 16].

34 In this article, we use algebraic geometry techniques (i.e., Groebner basis based implic-
35 itization algorithm) for computing the semi-algebraic representation of switching surfaces
36 (dependent purely on state-variables). We also construct a nested switching logic using
37 the computed expressions for these surfaces. Interestingly, unlike the earlier case (i.e.,
38 [5, 6]), the state-trajectory is forced into a limit cycle about the target by the optimal
39 feedback law for most non-origin target points. The period of this limit cycle is depen-
40 dent on the position of the target point in state-space. We characterize the time period
41 of the limit cycles thus created by the optimal control strategy. A preliminary version of
42 this article was presented in [10].

43 **2. Preliminaries and Analysis**

44 We consider a linear time invariant system with n -dimensional state-space:

$$\dot{x}(t) = Ax(t) + bu(t); \quad x(0) = x_0 \quad (1)$$

45 where $x : [0, \infty) \rightarrow \mathbb{R}^n$ is the state vector and the input $u(t)$ is a measurable function
 46 $u : [0, \infty) \rightarrow \mathbb{R}$ which belongs to a set of admissible inputs $U = \{u \in L^\infty[0, \infty) : |u(t)| \leq$
 47 $1 \text{ a.e. } t \in [0, \infty)\}$. We assume that the eigenvalues of matrix A are distinct and rational
 48 and the pair (A, b) is controllable. Let us denote by X_p the set of initial conditions from
 49 which system (1) can be transferred to $p \in \mathbb{R}^n$ in some time $t > 0$. We assume access to
 50 state-variables and compute the time optimal feedback law $h : X_p \rightarrow [-1, 1]$ to transfer
 51 any initial condition $x_0 \in X_p$ to the target point p . The eigenvalues of A are assumed to
 52 be distinct and rational. The *reachable set at time $t > 0$* (denoted by $R_p(t)$) to point p
 53 is the set of all the points $x \in \mathbb{R}^n$ that can be driven to p in time t using the admissible
 54 control $u(t) \in U$ [16].

$$R_p(t) = \left\{ e^{-At}p - \int_0^t e^{-A\tau}bu(\tau)d\tau : u(t) \in U \right\} \quad (2)$$

55 The set of all the states that can be driven to p using $u(t) \in U$ is called the *reachable*
 56 *set* to the point p and is $X_p = \bigcup_{t \in [0, \infty)} R_p(t)$. When p is the origin, we get the set of
 57 initial conditions $R_0(t)$ that can be driven to the origin with input $u(t) \in U$ in time t :
 58 $R_0(t) = \left\{ \int_0^t e^{-A\tau}bu(\tau)d\tau : u(t) \in U \right\}$. Then, the *set of null-controllable states* [12] is
 59 given by $X_0 = \bigcup_{t \in [0, \infty)} R_0(t)$. From point p the *attainable set* at time t is the set of all
 60 the states that can be reached from the point p using admissible control $u(t) \in U$ in time
 61 $t > 0$ [16].

$$\mathcal{A}_p(t) = \left\{ e^{At}p + \int_0^t e^{A(t-\tau)}bu(\tau)d\tau : u(t) \in U \right\} \quad (3)$$

62 Taking the union of set (3) for all time $t > 0$ we get the *attainable set* from the point p
 63 which is $\mathcal{A}_p = \bigcup_{t \in [0, \infty)} \mathcal{A}_p(t)$ [16].

64 A point $p \in \mathbb{R}^n$ is said to be a *constrained controllable* for system (1), if it is in
 65 the interior of X_p i.e. $x \in \text{int}(X_p)$. In other words all points in the neighborhood
 66 of a constrained controllable point p must be transferable to p . We restrict ourselves
 67 by considering the target states which are constrained controllable points because of

68 following reason. If a point p is not a constrained controllable point then for some initial
69 conditions in the neighbourhood of p it is impossible to *transfer* the state-trajectory to
70 target point p . Thus, such a target point is not useful for practical purposes. Hence-forth
71 we assume p to be a constrained controllable point.

Next we review the notion of switching surfaces, which will be used subsequently to
construct the time optimal feedback law. It is well known that the optimal control for
minimum time state-transfer is bang-bang with at most $n - 1$ switches [4]. Let $M_{p,k}^+$ be
the set of initial conditions which can be steered to the target p using bang-bang input
with at most $k - 1$ switches and initial input $u = 1$. To characterize the set $M_{p,k}^+$, we
first define the set $V_k := \{(t_1, t_2, \dots, t_k) : 0 \leq t_1 \leq t_2 \leq \dots \leq t_k < \infty\}$ for $k = 1, \dots, n$.
Next, we use (2) to define functions $F_{p,k}^+$ and $F_{p,k}^-$ as follows.

$$F_{p,k}^\pm : V_k \rightarrow \mathbb{R}^n$$

$$F_{p,k}^\pm : (t_1, \dots, t_k) \mapsto e^{-At_k} p \pm \left(- \int_0^{t_1} + \dots + (-1)^k \int_{t_{k-1}}^{t_k} \right) e^{-A\tau} b d\tau \quad (4)$$

72 Then, $M_{p,k}^+ = \{x : x = F_{p,k}^+(v), \forall v \in V_k\}$ and similarly, $M_{p,k}^-$ is the set of such conditions
73 with initial input $u = -1$ defined by $M_{p,k}^- = \{x : x = F_{p,k}^-(v), \forall v \in V_k\}$. Thus the set
74 of all states that can be driven to p in atmost $k - 1$ switches is defined as

$$M_{p,k} = M_{p,k}^+ \cup M_{p,k}^- \quad (5)$$

75 The sets $M_{p,k}$ for $k = 1, \dots, n$ obey the inclusion relation $M_{p,0} \subset M_{p,1} \subset \dots \subset M_{p,n}$.
76 From the existence and uniqueness of time optimal control to transfer any point in X_p
77 to the target point p (see [4]), we get $M_{p,n} = X_p$. In other words, the reachable set to
78 point p using only bang-bang input (with at most $n - 1$ switches) is in fact the entire
79 reachable set to p (i.e. X_p) and hence by (5), $X_p = M_{p,n}^+ \cup M_{p,n}^-$.

80 3. Using $M_{p,k}$ for Feedback

81 The nested sequence of sets $M_{p,k}$ ($k = 1, \dots, n - 1$) can be used to synthesize time op-
82 timal feedback control. Assume $p = 0$, temporarily, to simplify the following explanation.
83 To drive the system from any state in X_0 to $p = 0$ in minimum time, the control value
84 must ideally switch as follows. Consider $x_0 \in M_{0,n}^+$. Then initially, input $u = +1$ should

85 be applied, which pushes x from $M_{0,n}^+$ to the manifold $M_{0,n-1}^-$. As soon as $x \in M_{0,n-1}^-$,
 86 the input should switch to $u = -1$, which then pushes x to $M_{0,n-2}^+$ and so on. Finally
 87 input at $(n-1)^{th}$ switch pushes x from $M_{0,1}^+$ (if n is odd) or $M_{0,1}^-$ (if n is even) to the
 88 target $p = 0$. Similar sequence is valid for $x_0 \in M_{p,n}^-$ with opposite signs of input [6].
 89 This switching algorithm works ideally for $p = 0$, because the sets $M_{0,n}^+ \setminus M_{0,n-1}^+$ and
 90 $M_{0,n}^- \setminus M_{0,n-1}^-$ are disjoint and $M_{0,n}^+ \cap M_{0,n}^- = M_{0,n-1}$ is a set of measure zero in M_n
 91 (see [12]). Hence the initial input is determined uniquely from whether $x_0 \in M_{0,n}^+$ or
 92 $x_0 \in M_{0,n}^-$.

93 However, for most non-origin target points (i.e., $p \neq 0$), the set $M_{p,n}^+ \cap M_{p,n}^-$ is of non-
 94 zero measure in $M_{p,n}$. This implies that points in the set $M_{p,n}^+ \cap M_{p,n}^-$ can be driven to p
 95 by more than one, distinct bang-bang inputs with at most $n-1$ discontinuities. However,
 96 uniqueness of time-optimal control guarantees that only one of them is time-optimal. All
 97 points in the set X_p other than those which lie in the set $M_{p,n}^+ \cap M_{p,n}^-$, belong to exactly
 98 one of the sets $M_{p,n}^+$ or $M_{p,n}^-$. All the initial conditions $x_0 \in X_p \setminus (M_{p,n}^+ \cap M_{p,n}^-)$ can be
 99 driven to p in minimum time by using the time optimal switching (exactly as in $p = 0$
 100 case). The situation is demonstrated by an example next.

101 **Example 1.** For a second order LTI system (1) with $A = \text{diag}(1, 2)$, $b = [1 \ 1]^T$
 102 and $|u| \leq 1$, the corresponding structure of X_p with $p = \begin{bmatrix} 0.33 & 0 \end{bmatrix}^T$ is shown in Figure
 103 1. This figure illustrates that $M_{p,2}^+ \cap M_{p,2}^-$ is non-empty. For an initial condition $x_0 \in$
 104 $M_{p,2}^- \setminus (M_{p,2}^+ \cap M_{p,2}^-)$ shown in the figure, input $u = -1$ steers the state-trajectory $x(t)$
 105 towards $M_{p,1}^+$. As soon as $x(t) \in M_{p,1}^+$, the input $u = +1$ directs the state-trajectory
 106 towards p .

107 For initial conditions $x_0 \in M_{p,n}^+ \cap M_{p,n}^-$, we have two choices of initial control namely
 108 $u = +1$ and $u = -1$. Only one of them drives the system to p in minimum time.
 109 This initial choice can be computed beforehand by using PMP. However after the initial
 110 input has been applied, all the future control inputs are computed as per the algorithm
 111 proposed. If choice of initial input goes wrong, although time-optimality will be lost, the
 112 target point will be achieved in finite time.

113 Before giving an algorithm to compute $M_{p,k}$, we note that, for any real similarity

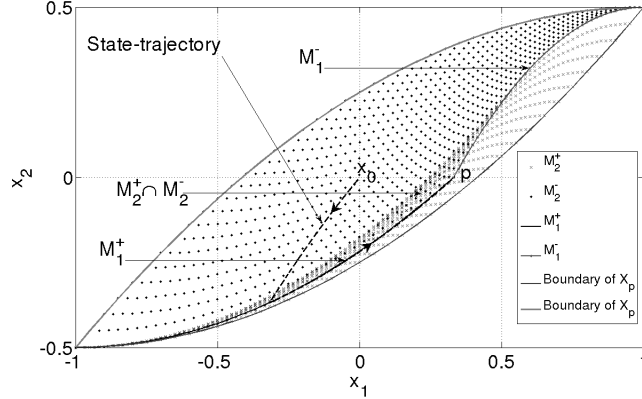


Figure 1: $X_0 = M_2^+ \cup M_2^-$ for case of Example 1

114 transformation $\hat{x} = Tx$ on a system, the corresponding set $\widehat{M}_{p,k}^\pm = \{\hat{x} = Tx : x \in$
 115 $M_{p,k}^\pm\}$ [12]. As system matrix A has distinct rational eigenvalues, we assume A to be
 116 diagonal without loss of generality.

117 4. Parametric Representation

118 All $x \in M_{p,k}$ are characterized by the functions $F_{p,k}^+$ or $F_{p,k}^-$ (given by (4)) defined
 119 over V_k . Note that A is assumed to be diagonal. To use $M_{p,k}$ for state based switching
 120 we must eliminate variables t_1, \dots, t_k from (4). For that purpose we first convert the
 121 expressions defining $M_{p,k}$ to polynomial and rational functions by suitable substitution
 122 of variables. First we assume that all the eigenvalues of matrix A are non-zero. However,
 123 if any eigenvalue turns out to be zero then a similar process is valid, albeit with a slight
 124 modification which is discussed later in this section. Note that since the eigenvalues of
 125 A are assumed to be distinct, repeated zero eigenvalues are not allowed.

126 4.1. All the eigenvalues of A are non-zero:

We rewrite the state variables x_i , $i = 1, \dots, n$ defined by (4) as: $x_i = f_{p,k,i}^\pm(e^{-\lambda_i t_1}, \dots,$
 $e^{-\lambda_i t_k})$ for $i = 1, \dots, n$ where $\lambda_i \in \lambda(A)$. Here $f_{p,k,i}^\pm$ denotes the i^{th} component of
 function $F_{p,k}^\pm$ defined by (4). Also, since A is assumed to be diagonal $f_{p,k,i}^\pm$ depends
 only on the i^{th} eigenvalue of A i.e., λ_i . Let the first q eigenvalues $\lambda_1, \dots, \lambda_q$ be positive
 and the remaining $n - q$ eigenvalues $\lambda_{q+1}, \dots, \lambda_n$ be negative. Since $\lambda_i \in \mathbb{Q}$, we write
 $\lambda_i = \frac{n_i}{d_i}$ for $i = 1, \dots, n$, where n_i and d_i are co-prime. Let $l = \text{lcm}(d_1, \dots, d_n)$ be the

least common multiple of d_1, \dots, d_n . Then by substituting $z_j = e^{-\frac{t_j}{t}} \forall j = 1, \dots, k$ we get, $x_i = f_{p,k,i}^+(z_1^{p_i}, \dots, z_k^{p_i})$, $i = 1, \dots, q$ and $x_i = f_{p,k,i}^+(z_1^{-p_i}, \dots, z_k^{-p_i})$, $i = q+1, \dots, n$. Here $p_i = |\lambda_i l|$. Thus x_i 's for $i = 1, \dots, q$ are now polynomials in z_1, \dots, z_k and for $i = q+1, \dots, n$, x_i 's are rational functions in z_1, \dots, z_k . Hence, in general, we write $x_i = \frac{N_{p,k,i}^+(z_1, \dots, z_k)}{D_{p,k,i}^+(z_1, \dots, z_k)}$, $i = 1, \dots, n$ where $\frac{N_{p,k,i}^+}{D_{p,k,i}^+} = f_{p,k,i}^+$ and $D_{p,k,i}^+ = 1$ for $i = 1, \dots, q$. This gives rational parametric representations of $M_{p,k}^+$ and $M_{p,k}^-$:

$$M_{p,k}^+ = \{(x_1, \dots, x_n) : x_i = \frac{N_{p,k,i}^+(z_1, \dots, z_k)}{D_{p,k,i}^+(z_1, \dots, z_k)} \forall i = 1, \dots, n, 0 < z_k \leq z_{k-1} \leq \dots \leq z_1 \leq 1\} \quad (6)$$

127 Note that the eigenvalues of A can be of mixed signs. Specifically if all eigenvalues of
 128 A have same signs then by appropriately substituting either $z_j = e^{-\frac{t_j}{t}}$ or $z_j = e^{\frac{t_j}{t}}$, we
 129 can obtain a polynomial parametric representation where $D_{p,k,i}^+ = 1$ for all $i = 1, \dots, n$.
 130 The variables z_1, \dots, z_k must be eliminated from (6) to represent $M_{p,k}^+$ and $M_{p,k}^-$ purely
 131 in terms of the state variables x_1, \dots, x_n . Such a representation can then be used directly
 132 for a state-feedback based switching of the input values between ± 1 . For that we use the
 133 Groebner basis based elimination method which is described in Section 5.1.

134 4.2. One eigenvalue of A is zero:

135 Without loss of generality we assume that zero eigenvalue corresponds to the state
 136 x_n . The first $n-1$ state variables are rewritten identically as described above. But,
 137 the remaining state variable x_n is a linear function in variables t_1, \dots, t_k given by $x_n =$
 138 $\pm(2t_1 - 2t_2 + \dots + (-1)^{k-1}2t_{k-1} + (-1)^k t_k)$. For the sake of simplicity we assume k to be
 139 even. Then, $x_n = +(2t_1 - 2t_2 + \dots + (-1)^{k-1}2t_{k-1} + t_k)$. At this stage, since x_n is linear
 140 in its arguments, we eliminate one variable (say t_1) from variables t_1, \dots, t_k as follows:

141 1. Substitute $t_1 = \frac{1}{2}(x_n - \sum_{j=2}^{k-1} 2(-1)^{j-1}t_j + (-1)^{k-1}t_k)$ in the functions describing
 142 x_i for all $i = 1, \dots, n-1$.

143 2. Then x_i for $i = 1, \dots, n-1$ becomes

$$x_i = f_{p,k,i}^+ \left(\frac{e^{-\frac{1}{2}\lambda_i x_n} \prod_{q=1}^{\frac{k-2}{2}} e^{-\lambda_i t_{2q+1}}}{e^{-\frac{1}{2}\lambda_i t_k} \prod_{q=1}^{\frac{k-2}{2}} e^{-\lambda_i t_{2q}}}, e^{-\lambda_i t_2}, \dots, e^{-\lambda_i t_k} \right) \quad (7)$$

144 Recall that, $\lambda_i \in \mathbb{Q}$. Hence we write $\lambda_i = \frac{n_i}{d_i}$ for $i = 1, \dots, n-1$. Let $l = \text{lcm}(d_1, \dots, d_{n-1})$
145 be the least common multiple of d_1, \dots, d_{n-1} . We convert the above function (defined by
146 (7)) into polynomials or rational function by substituting $z_j = e^{-\frac{t_j}{l}} \forall j = 2, \dots, k-1$ and
147 $w = e^{-\frac{x_n}{l}}$. After substitution, $x_i = f_{p,k,i}^+ \left(\frac{w^{-\frac{1}{2}p_i} \prod_{q=1}^{\frac{k-2}{2}} z_{2q+1}^{-p_i}}{z_k^{-\frac{1}{2}p_i} \prod_{q=1}^{\frac{k-2}{2}} z_{2q}^{-p_i}}, z_2^{p_i}, \dots, z_k^{p_i} \right)$, $i = 1, \dots, q$
148 and $x_i = f_{p,k,i}^+ \left(\frac{w^{\frac{1}{2}p_i} z_k^{-\frac{1}{2}p_i} \prod_{q=1}^{\frac{k-2}{2}} z_{2q}^{-p_i}}{\prod_{q=1}^{\frac{k-2}{2}} z_{2q+1}^{-p_i}}, z_2^{-p_i}, \dots, z_k^{-p_i} \right)$ for $i = q+1, \dots, n-1$. Here $p_i = |\lambda_i l|$
149 is a positive integer for $i = 1, \dots, n-1$. Thus, we write,

$$x_i = \frac{N_{p,k,i}^+(z_2, \dots, z_k, w)}{D_{p,k,i}^+(z_2, \dots, z_k, w)}, \quad i = 1, \dots, n-1 \quad (8)$$

150 and,

$$x_n = (-2\log z_1 + \dots + (-1)^{k-2} 2\log z_{k-1} + 2\log z_k) \quad (9)$$

where $w = e^{-\frac{x_n}{l}}$. Similar, expression for x_i easily follows for an odd numbered k . Note that (9) is not in polynomial or rational form. However the state variables x_i for $i = 1, \dots, n-1$ are in rational parametric form in variables z_2, z_3, \dots, z_k, w (see (8)). This gives the following parametric representations of $M_{p,k}^+$ and $M_{p,k}^-$:

$$M_{p,k}^+ = \{(x_1, \dots, x_n) : (8) \text{ and } (9) \text{ hold} \\ \text{and } 0 < z_k \leq \dots \leq z_2 \leq 1\} \quad (10)$$

151 Since we have obtained (8) by already eliminating t_1 (i.e. z_1) we now proceed to elimi-
152 nate variable z_2, z_3, \dots, z_k from (8) to form an implicit representation involving only state
153 variables x_1, \dots, x_{n-1} and $w = e^{-\frac{x_n}{l}}$.

154 *Remark 2.* Note that the set $M_{p,k}^+$ is not algebraic, since the terms in (9) are logarithmic.
155 Now (8) is obtained by eliminating the variable t_1 , and we only consider (8) for future
156 computations. If we treat w as a separate variable, (8) can be considered as a rational
157 function in variables z_2, z_3, \dots, z_k, w . Hence, the Groebner basis computation required for
158 implicitly describing switching surfaces remains identical to the previous case.

159 **5. Switching Surface and Switching algorithm**

160 The computation of switching surfaces by elimination (using Groebner basis) of vari-
 161 able z_1, \dots, z_{n-1} from the parametric description of the set $M_{p,n-1}^\pm$ was presented in [5]
 162 and [6]. Here, we recount the elimination procedure for the sake of completeness.

163 *5.1. Implicitization*

164 We have following parametric representation for switching surface $M_{p,n-1}^+$:

$$x_i = \frac{N_{p,n-1,i}^+(z_1, \dots, z_{n-1})}{D_{p,n-1,i}^+(z_1, \dots, z_{n-1})}, \quad i = 1, \dots, n \quad (11)$$

165 with z_1, \dots, z_{n-1} satisfying the inequality

$$0 < z_{n-1} \leq z_{n-2} \leq \dots \leq z_1 \leq 1 \quad (12)$$

166 First, we follow standard implicitization steps to eliminate the variables z_1, \dots, z_{n-1}
 167 from (11) (see [17]). For simplicity of notation, we drop the subscript p from $N_{p,n-1}^+$ and
 168 $D_{p,n-1}^+$. The procedure is as follows.

169 1) Using (11) form an ideal $J_{p,n-1}^+ = \langle D_{n-1,1}^+x_1 - N_{n-1,1}^+, \dots, D_{n-1,n}^+x_n - N_{n-1,n}^+, 1 -$
 170 $D_{n-1,1}^+D_{n-1,2}^+\dots D_{n-1,n}^+y \rangle$. The additional element $1 - D_{n-1,1}^+D_{n-1,2}^+\dots D_{n-1,n}^+y$ is added
 171 in order to prevent the denominators $D_{n-1,1}^+, \dots, D_{n-1,n}^+$ from becoming zero. Note that
 172 $J_{p,n-1}^+ \subset \mathbb{Q}[y, z_1, \dots, z_{n-1}, x_1, \dots, x_n]$.

173 2) Compute Groebner basis $G_{p,n-1}^+$ of $J_{p,n-1}^+$ w.r.t. lexicographic ordering as $y \succ$
 174 $z_1 \succ z_2 \succ \dots \succ z_{n-1} \succ x_1 \succ \dots \succ x_n$.

175 3) The element $g_{p,n-1}^+ \in G_{p,n-1}^+ \cap \mathbb{Q}[x_1, \dots, x_n]$ (i.e., the element in $G_{p,n-1}^+$ not
 176 involving variables y, z_1, \dots, z_{n-1}) defines the smallest variety containing the parametric
 177 representation (11).

178 *Remark 3.* If one eigenvalue of A is zero, we follow exactly the same steps while treating
 179 w as a separate variable. We eliminate variables z_2, \dots, z_{n-1} from $n - 1$ equations and
 180 then substitute $w = e^{-\frac{x_n}{t}}$ in the Groebner basis $G_{p,n-1}^+$.

181 Next, we express inequality (12) purely in terms of state-variables x_1, \dots, x_n by solving
 182 for the variables z_1, \dots, z_{n-1} . The procedure is as follows. In the description of set $M_{p,n-1}^+$
 183 let us denote the respective z_i by z_i^+ ($i = 1, \dots, n - 1$). To solve for a parameter z_k^+ :

184 1) Compute the Groebner basis (say G_{p,z_k}^+) using the lexicographic ordering $.. \succ .. \succ$
 185 $... \succ z_k^+ \succ x_1 \succ ... \succ x_n$. Note that in this ordering all parameters other than z_k^+ i.e.,
 186 z_i^+ ($i = 1, \dots, n-1$ and $i \neq k$) are ordered higher (and z_k^+ itself is ordered higher than
 187 all state variables).

188 2) Consider the set $G_{p,z_k}^+ \cap \mathbb{Q}[z_k^+, x_1, \dots, x_n]$ and let there be m elements denoted by
 189 $g_{p,j}^+ = 0 \quad \forall j = 1, \dots, m$ in this set. These elements are polynomials that have pure terms
 190 in variables (z_k^+, x_1, \dots, x_n) .

191 3) Now, if among these m polynomials i.e., $g_{p,j}^+ = 0 \quad \forall j = 1, \dots, m$, at least one
 192 polynomial has all the monomials involving z_k^+ with same power then, we express z_k^+ as
 193 a closed form expression in terms of x_1, \dots, x_n .

194 4) Otherwise, to check whether current state (x_1, \dots, x_n) satisfies (12) we solve single
 195 variable polynomial equation with z_k^+ as the only variable.

196 5) Repeat steps 1 to 4 for all parameters z_1^+, \dots, z_{n-1}^+ and check whether any set of
 197 the solutions $z_i^+, i = 1, \dots, n-1$ satisfies (12).

198 *Remark 4.* Note that all the intensive computations in the procedure (i.e elimination of
 199 variables using Groebner basis) are being done off-line. The only on line computation
 200 required is that of evaluating multivariate polynomials and solving single variable poly-
 201 nomials (if required). The case of solving single variable polynomials arise only if z_k^+ for
 202 any $k = 1, \dots, n-1$ does not have a closed form expression in terms of x_1, \dots, x_n .

203 5.2. Switching algorithm

204 Now using the expressions obtained above, we can check if a point x in the state-
 205 space belongs to the switching surface $M_{p,n-1}$. We first note that since $M_{p,n-1}$ is a
 206 set of measure zero in $M_{p,n}$, generically $x_0 \in M_{p,n} \setminus M_{p,n-1}$. As discussed in section
 207 2 we must first compute the initial input $u(0)$ (which can be computed by checking
 208 $x_0 \in M_{p,n}^\pm \setminus M_{p,n-1}$). As per the switching logic described in Section 2, ideally, the sign
 209 of the input should change as soon the state trajectory has reached $M_{p,n-1}$. Since we
 210 now have an expression for $M_{p,n-1}$ in terms of state variables, whether $x \in M_{p,n-1}$ can
 211 be checked continuously. Now, the state trajectory will travel along $M_{p,n-1}$ until it hits
 212 $M_{p,n-2}$. This will carry on for all $M_{p,k}$ with $k < n-2$. Hence, it appears that for
 213 realizing the optimal switching ideally, we need to compute $M_{p,k}$ for all $k = 0, \dots, n-1$

214 and check whether $x(t) \in M_{p,k}$ for $k < n$ instantaneously. This optimal switching law
 215 can be stated by the following function

$$h(x) = \begin{cases} +1 & \text{if } x \in M_{p,k}^+ \setminus M_{p,k-1} \text{ for } k = 1, \dots, n-1 \\ -1 & \text{if } x \in M_{p,k}^- \setminus M_{p,k-1} \text{ for } k = 1, \dots, n-1 \end{cases}$$

216 However, in simulation or practice, unavoidable delays in computation (say δ) would
 217 make the state-trajectory to overshoot $M_{p,n-1}$ and enter $M_{p,n} \setminus M_{p,n-1}$ slightly as soon
 218 as the first switch occurs. Now, as the state trajectory is in $M_{p,n} \setminus M_{p,n-1}$, we can reuse
 219 $M_{p,n-1}$ for the second switch. This situation repeats for all the $n-1$ switches and the
 220 knowledge of $M_{p,n-1}$ is enough to construct the entire switching law. Hence, we use the
 221 implicit description of $M_{p,n-1}$ to implement the switching logic using algorithm 1.

Algorithm 1 Switching logic

Require: current $x(t)$ and past ($u(t)$)

if $x(t) \in M_{p,n-1}$ **then**

$$u(t + \delta) = -u(t)$$

else

$$u(t + \delta) = u(t)$$

end if

222 *5.3. Examples*

223 **Example 5.** Consider system of the form (1) with $A = \text{diag}(1, 2, 3)$ and $b = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}^T$.

224 Let the target state be $p = \begin{bmatrix} 0.1 & 0.1 & 0.1 \end{bmatrix}^T$. We compute the parametric expres-
 225 sion for states using (4). By substituting $z_i = e^{-t_i}$ we convert this parametric ex-

226 pression F_2^+ into a polynomial form. The resulting expression along the inequalities

227 $0 \leq z_2 \leq z_1 \leq 1$ describe the surface M_2^+ . Then to eliminate z_1 and z_2 we first form an

228 ideal $J^+ = \langle x_1 - 2z_1 + \frac{9}{10}z_2 + 1, x_2 - z_1^2 + \frac{2}{5}z_2^2 + \frac{1}{2}, x_3 - \frac{2}{3}z_1^3 + \frac{7}{30}z_2^3 + \frac{1}{3} \rangle$ from the polynomials

229 of F_2^+ . The Groebner basis G^+ with ordering $z_2 \succ z_1 \succ x_1 \succ x_2 \succ x_3$ for the ideal J^+ is

230 calculated¹. Due to lack of space we omit the Groebner basis. We select an element from

231 Groebner basis which is only in terms of state variables x_1, x_2 and x_3 . Let us denote it by

¹Computed using a computer algebra package Singular[18]

232 $g_{p,2}^+(x_1, x_2, x_3)$. Now, $g_2^+(x_1, x_2, x_3) = 0$ and condition $0 < z_2 \leq z_1 \leq 1$ together describe
233 M_2^+ . Further, we also select an element from Groebner basis which is linear in z_1 . Solv-
234 ing this equation gives $z_1 = -\frac{-\frac{2675}{8014}x_1^3 - \frac{8025}{8014}x_1^2 + \frac{22}{4007}x_1x_2 - \frac{8003}{8014}x_1 + \frac{22}{4007}x_2 + \frac{168507}{160280}x_3 + \frac{3109}{160280}}{x_1^2 + 2x_1 - \frac{163609}{80140}x_2 - \frac{3329}{160280}}$.
235 Similar expression for z_2 can be found from the Groebner basis of ideal J with ordering
236 $z_1 \succ z_2 \succ x_1 \succ x_2 \succ x_3$. Thus, we get $M_{p,2}^+ = \{(x_1, x_2, x_3) : g_{p,2}^+(x_1, x_2, x_3) = 0, 0 <$
237 $z_2 \leq z_1 \leq 1\}$. Similarly, $M_{p,2}^-$ can be calculated. The feedback logic can be implemented
238 as per algorithm 1. We compare the switching instants generated using algorithm 1 with
239 those generated by optimal open loop input computed using PMP for the sample ini-
240 tial condition, $x_0 = \begin{bmatrix} -0.2 & -0.14 & -0.1 \end{bmatrix}^T$. The initial value of the optimal input is
241 $u(0) = +1$ and the optimal open-loop switching instants are $t_1 = 0.0704$ and $t_2 = 0.1953$.
242 At $t_3 = 0.6419$ the system reaches p . We infer that the respective open loop switching
243 instants are matching with the closed loop switching instants.

244 6. Limit Cycles

245 For the origin target point, it was shown in [5, 6] that the trajectory can not only be
246 transferred to the origin but also kept within any arbitrarily small neighborhood of the
247 origin by accurate switching. However, for almost all the target points, the trajectory,
248 after passing through the target goes into a limit cycle (about the target). This limit
249 cycle appears due to the difference in the relative directions of the vector fields associated
250 with the two inputs (± 1) at the target point. In this section, we analyze the conditions
251 for occurrence of such a limit cycle and propose an algorithm to characterize the period
252 of the limit cycle.

253 6.1. Existence of a Limit Cycle

254 The switching algorithm proposed in Section 5 repeatedly forces the state trajectory
255 back to the target p every time it overshoots p . This gives rise to a limit cycle about the
256 target point p . We illustrate the situation by following example.

257 **Example 6.** Consider Example 1 from Section 2 with the target state $p = [0.1 \ 0]^T$.
258 Figure 2 shows the phase diagram corresponding to the state-trajectory starting with
259 the initial condition $x_0 = [0.2 \ 0]^T$.

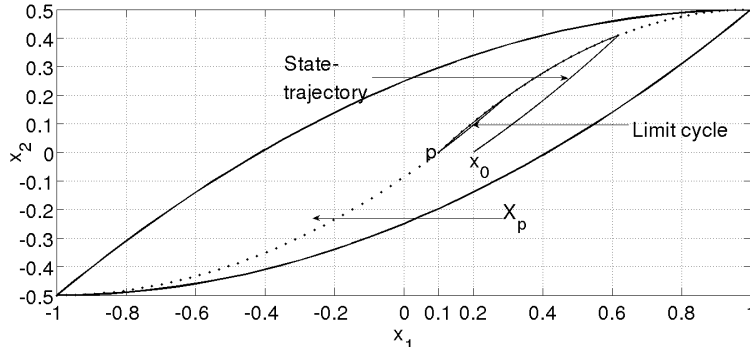


Figure 2: The limit cycle near $p = [0.1 \ 0]^T$

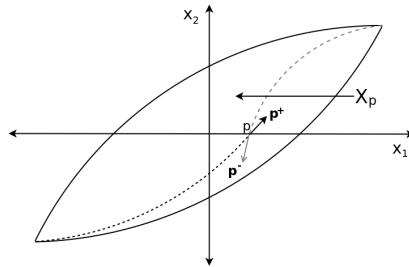


Figure 3: The vector fields corresponding to the two inputs ± 1

260 From Figure 2, we observe that the state-trajectory after reaching the point p is forced
 261 into a limit cycle (with a period of 0.410 seconds). This happens because the switching
 262 curve is not smooth at the target p . We illustrate this by Figure 3 where the velocity
 263 vectors \mathbf{p}^+ and \mathbf{p}^- corresponding to the two inputs ± 1 are not exactly opposed to one
 264 another and hence the switching curve is non-smooth at point p . Therefore, after reaching
 265 p and overshooting slightly into $M_{p,2}^+$, the state trajectory is forced (by algorithm 1) in
 266 the direction of \mathbf{p}^+ until it reaches the switching surface again. The next input switch
 267 at this instant brings it back to p along the switching curve. This repetition results in a
 268 limit cycle.

269 6.2. Non occurrence of limit cycle for some target points

270 If the switching curve is smooth at the target point p , then the state-trajectory
 271 does not form a limit cycle. We analyze this situation using the concept of average
 272 velocity (Chapter 3, Section 1.1 of [19]). Let the input to the system be $u = 1$ for
 273 time Δt_1 followed by $u = -1$ for time Δt_2 . Now, the change in the state value Δx

274 in time $\Delta t = \Delta t_1 + \Delta t_2$ is given by $\Delta x = \dot{x}_+ \Delta t_1 + \dot{x}_- \Delta t_2$ (where $\dot{x}_+ = Ax + b$ and
275 $\dot{x}_- = Ax - b$). Assuming $\Delta t_1 = \alpha \Delta t$ for some $\alpha \in (0, 1)$ we get, $\frac{\Delta x}{\Delta t} = \alpha \dot{x}_+ + (1 - \alpha) \dot{x}_-$.
276 We define the *average velocity* as $\dot{x}_{avg} = \alpha \dot{x}_+ + (1 - \alpha) \dot{x}_-$ by taking limit as $\Delta t \rightarrow 0$.
277 The state trajectory can be kept in an arbitrarily small neighbourhood of the target
278 point, if and only if there exists $\alpha \in (0, 1)$ such that $\dot{x}_{avg} = 0$ at the target p (Chapter
279 3, Section 1.1 of [19]). Now, $\dot{x}_{avg} = \alpha \dot{x}_+ + (1 - \alpha) \dot{x}_- = 0$ i.e. \dot{x}_+ and \dot{x}_- are linearly
280 dependent and are pointing in opposite direction. Hence, $Ax + b = -\frac{1-\alpha}{\alpha}(Ax - b)$.
281 Therefore all the target points which do not impose limit cycle are characterized by the
282 set $L_0 := \{x | Ax = (1 - 2\alpha)b, \text{ for some } 0 < \alpha < 1\}$. For points not lying in the set L_0 ,
283 there does not exist any $\alpha \in (0, 1)$ to create $\dot{x}_{avg} = 0$. Therefore, for such points the
284 limit cycle is unavoidable.

285 6.3. Time period of the Limit Cycle

286 We now compute the time period of limit cycle for points $x \in X_p \setminus L_0$. By sub-
287 stituting the initial condition $x_0 = p$ in (4), we get $p = e^{-At_n} p \pm (-\int_0^{t_1} + \int_{t_1}^{t_2} - \dots +$
288 $(-1)^n \int_{t_{n-1}}^{t_n} e^{-A\tau} b d\tau)$ and $(I - e^{-At_n})p = F_{0,n}^\pm(t_1, \dots, t_n)$.

289 **Definition 7.** The set of all the target points which gives rise to a limit cycle of time
290 period $t_n \leq T$ is given by, $L_T = \{p | (I - e^{-At_n})p = F_{0,n}^\pm(t_1, \dots, t_n) : 0 < t_1 \leq \dots \leq t_n \leq T\}$.

291 The boundary of this set L_T is $\partial L_T = \{p | (I - e^{-AT})p = F_{0,n}^\pm(t_1, \dots, t_{n-1}, T); 0 < t_1 \leq$
292 $\dots \leq t_{n-1} \leq T\}$.

293 **Lemma 8.** For $T_1 > T_2$, $L_{T_2} \subset L_{T_1}$.

294 **Theorem 9.** L_T is a convex set.

295 *Proof.* We consider two cases. 1) *Matrix A has non-zero eigenvalues:* $R_0(T)$ is a convex
296 set [12]. We observe from the definition of ∂L_T that $(I - e^{-AT})^{-1} \partial R_0(T) = \partial L_T$ and
297 $(I - e^{-AT})^{-1} R_0(T) = L_T$. Also, for all $T_1 < T_2 < T$, $R_0(T_1) \subset R_0(T_2) \subset R_0(T)$ [12].

298 Now, by convexity of $R_0(T)$, we have

$$\bigcup_{\lambda \in [0,1]} (\lambda \partial R_0(T_1) + (1 - \lambda) \partial R_0(T_2)) = R_0(T_2)$$

299 Thus,

$$\bigcup_{\lambda \in [0,1]} ((I - e^{-AT_2})^{-1} (\lambda \partial R_0(T_1) + (1 - \lambda) \partial R_0(T_2))) = L_{T_2}$$

300 and hence,

$$\bigcup_{\lambda \in [0,1]} \lambda(I - e^{-AT_2})^{-1} \partial R_0(T_1) + (1 - \lambda) \partial L_{T_2} = L_{T_2} \subset L_T. \quad (13)$$

301 But, $\partial R_0(T_1) \subset R_0(T_2)$. Thus, $(I - e^{-AT_2})^{-1} \partial R_0(T_1) \subset L_{T_2} \subset L_T$. Now, choose any
 302 $p_1, p_2 \in L_T$. For these points p_1 and p_2 there exist $T_1 < T$ and $T_2 < T$ respectively such
 303 that $p_1 \in [I - e^{-AT_2}]^{-1} \partial R_0(T_1) \subset L_T$ and $p_2 \in \partial L_{T_2} \subset L_T$. By (13), it follows that
 304 $\lambda p_1 + (1 - \lambda) p_2 \in L_T$ for all $\lambda \in [0, 1]$.

305 2) *Matrix A has one zero eigenvalue* ($\lambda_n(A) = 0$): Without loss of generality, we
 306 consider $A = \begin{bmatrix} \tilde{A} & 0 \\ 0 & 0 \end{bmatrix}$ where $\tilde{A} \in \mathbb{R}^{(n-1) \times (n-1)}$ is a diagonal matrix. Let

$$F_{0,n}^{\pm}(t_1, \dots, t_n) = \begin{bmatrix} \tilde{F}_{0,n}^{\pm}(t_1, \dots, t_n) \\ \pm \sum_{i=1}^{n-1} 2(-1)^i t_i + (-1)^{n-1} t_n \end{bmatrix}$$

307 Then, $\tilde{R}_0(T) = \{x \in \mathbb{R}^{n-1} : x = \tilde{F}_{0,n}^{\pm}(t_1, \dots, t_n), 0 < t_1 \leq \dots \leq t_n \leq T\}$ i.e. $\tilde{R}_0(T)$
 308 is a projection of $R_0(T)$ on hyperplane $x_n = 0$. Therefore, $\tilde{R}_0(T)$ is also a convex set.
 309 Let $\tilde{L}_T = \{\tilde{p} \in \mathbb{R}^{n-1} | \tilde{p} = (\tilde{I} - e^{-\tilde{A}t_n})^{-1} \tilde{F}_{0,n}^{\pm}(t_1, \dots, t_n), 0 < t_1 \leq \dots \leq t_n \leq T\}$. Now,
 310 $L_T = \tilde{L}_T \times \langle e_n \rangle$ (where $\langle e_n \rangle$ is span of $e_n = \begin{bmatrix} 0 & 0 & \dots & 1 \end{bmatrix}^T$ i.e. the n^{th} standard
 311 unit vector and symbol \times denotes Cartesian product of two sets). Then since $\tilde{R}_0(T)$ is
 312 a convex set \tilde{L}_T is also a convex set (using same arguments as in case 1). Hence, L_T is
 313 a convex set. \square

314 We convert the representation of L_T^{\pm} to rational or polynomial parametric repre-
 315 sentation (depending on eigenvalues of A) using the procedures described in Section 4.
 316 Compute Groebner basis G_n^+ and G_n^- for L_T^+ and L_T^- respectively using standard implic-
 317 itization steps described in Section 5. Using the computed Groebner basis G_n^+ and G_n^- ,
 318 we compute the time period of limit cycle for the given target p . We also provide an
 319 easy to check sufficient condition to test whether a target point $p \in L_T$ for a given time
 320 period T .

321 *6.3.1. Computation of time period*

322 The time period of the limit cycle for a given target point p is computed as fol-
 323 lows. First select $g_n^+ \in G_n^+[z_n, p_1, \dots, p_n]$ and solve $g_n^+ = 0$ for z_n . Then select $g_{n-1}^+ \in$
 324 $G_n^+[z_n, z_{n-1}, p_1, \dots, p_n]$ and using the values of z_n obtained in the previous step, solve
 325 $g_{n-1}^+ = 0$ for z_{n-1} and so on. Lastly, select $g_1^+ \in G_n^+[z_n, z_{n-1}, \dots, z_1, p_1, \dots, p_n]$ and using
 326 values of z_n, z_{n-1}, \dots, z_2 obtained in previous step, solve $g_1^+ = 0$ for z_1 . Repeat the above
 327 procedure for G_n^- . We obtain several solutions for z_1, z_2, \dots, z_n . Now, among these solu-
 328 tions select the one that satisfies the inequality $0 < z_n \leq z_{n-1} \leq \dots \leq z_1 \leq 1$. Then,
 329 $t_i = -l \log(z_i)$ for $i = 1, \dots, n-1$ are the switching instants of limit cycle about p . The
 330 *time period of limit cycle is* $T = t_n = -l \log(z_n)$ (refer to Section 4).

331 For the case of one zero eigenvalue, first compute the values of z_n, z_{n-1}, \dots, z_2 using
 332 first $n-1$ steps described above. Finally to compute t_1 we use $x_n = \pm(2t_1 - 2t_2 + \dots +$
 333 $(-1)^{k-1}2t_{n-1} + (-1)^k t_n)$ where $t_i = -l \log z_i$. Among several solutions thus obtained, we
 334 choose, in particular, the solution t_1, t_2, \dots, t_n satisfying $0 \leq t_1 \leq t_2 \leq \dots \leq t_n < \infty$.
 335 Then the *time period of limit cycle is* $T = t_n$.

336 *6.3.2. Characterizing L_T*

337 Next we characterize the set of points p that gives rise to a limit cycle of period T
 338 i.e. ∂L_T . Substitute $z_n = e^{-\frac{T}{l}}$. Then the equation $g_n^+(z_n, p_1, \dots, p_n) = 0$ describes the
 339 smallest variety containing the parametric representation of ∂L_T^+ for a given period T .
 340 Similarly, the equation $g_n^-(z_n, p_1, \dots, p_n) = 0$ describes the smallest variety containing the
 341 parametric representation of ∂L_T^- . The following sufficient condition provides an easy
 342 test to check whether $x \in L_T$:

343 **Theorem 10.** *If for all $\mu \in [0, 1]$, $g_n^+(\mu p) \neq 0$ and $g_n^-(\mu p) \neq 0$ then $p \in L_T$.*

344 *Remark 11.* From the sequence of switching events described at the end of Section 2,
 345 we conclude that for odd ordered systems (i.e n is odd) limit cycle trajectory follows the
 346 sequence $p \rightarrow M_n^\pm \rightarrow M_{n-1}^\mp \rightarrow \dots \rightarrow M_1^\pm \rightarrow p \rightarrow M_n^\pm$. Similarly for even ordered system
 347 (i.e. n is even) limit cycle trajectory follows the sequence $p \rightarrow M_n^\pm \rightarrow M_{n-1}^\mp \rightarrow \dots \rightarrow$
 348 $M_1^\mp \rightarrow p \rightarrow M_n^\pm$. We observe that for odd ordered system control input value does not
 349 change its sign at the target point p whereas for even ordered system change of sign in
 350 control input value occurs at the target point p .

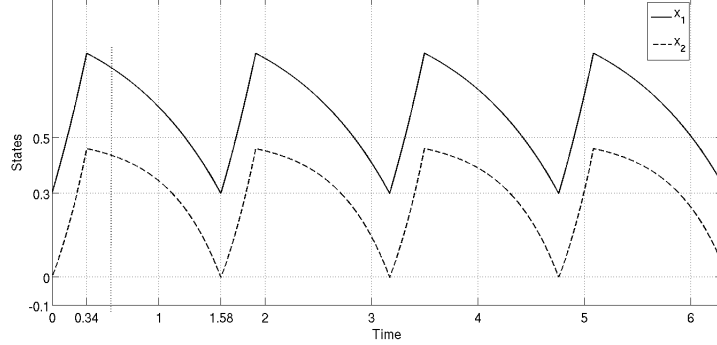


Figure 4: Limit cycle with $p = [0.3 \ 0]^T$ and period $t = 1.5833$

351 **Example 12.** Consider the system from Example 1, Section 2. For the target point
352 $p = [p_1 \ p_2]^T$, we substitute $z_i = e^{-t_i}$ to get polynomial equations in p_1 and p_2 . Moreover
353 the inequality $0 < t_1 \leq t_2 < \infty$ is converted to $0 < z_2 \leq z_1 < 1$. Using the procedure
354 described above we eliminate z_1 and obtain G_2^+ as $s_1 = z_2^2 p_1^2 - 2z_2^2 p_1 + 4z_2^2 p_2 - z_2^2 -$
355 $2z_2 p_1^2 + 2z_2 + p_1^2 + 2p_1 - 4p_2 - 1$ and $s_2 = 2z_1 + z_2 p_1 - z_2 - p_1 - 1$. Here $g_2^+ = s_1$.
356 Similarly, we can find g_2^- using $u = -1$ for $0 \leq t \leq t_1$ and then switching accordingly.
357 For $p = [0.3 \ 0]^T$, solution of $g_2^+ = 0$ gives $(1.51z_2 - 0.31)(z_2 - 1) = 0$. The solution
358 $z_1 = 1$ is not a meaningful solution since it gives a limit cycle of period $t_2 = 0$. The
359 solution $z_2 = \frac{31}{151}$, gives $z_1 = \frac{218}{302}$ and the inequality $0 < z_2 \leq z_1 < 1$ is satisfied by this
360 solution. Hence at $p = [0.3 \ 0]^T$, we get a limit cycle with period $t_2 = 1.5833$. This can
361 be verified from Figure 4.

362 Also for a given period say $t_2 = T = 1$ the set of all points p around which the
363 state trajectory goes into a limit cycle of period $T = 1$ with starting input $u = 1$ can be
364 computed from g_2^+ . For $t_2 = 1$, we have $z_2 = e^{(-1)} = 0.3679$. With this z_2 , $s_1 = 0$ gives
365 $p_1^2 + 4.3276p_1 - 8.6554p_2 - 1 = 0$. Similarly, for starting input $u = -1$, the set of such
366 points can be calculated from g_2^- . This set is shown in Figure 5.

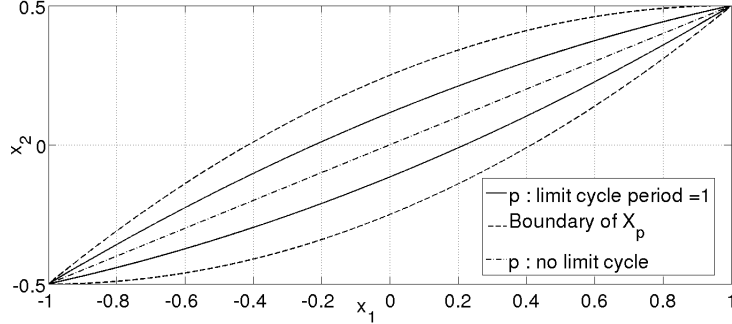


Figure 5: Set of points p around which limit cycle has period 1

367 7. Constrained Controllable and Reachable Sets

368 Let $CCP = \{p \in \mathbb{R}^n : p \in \text{int } X_p\}$ be the set of all constrained controllable points
 369 for (1). In this section we describe an algebraic method to compute CCP . Recall the
 370 definition of the null controllable set X_0 and the attainable set \mathcal{A}_0 from Section 2. We
 371 call a system *semi-stable* if all eigenvalues of A lie in closed left half of the complex
 372 plane (i.e., $\lambda(A) \leq 0$). Otherwise (i.e., if $\lambda(A) > 0$) we call the system *anti-stable*.
 373 Under the assumption that system (1) is controllable, the set CCP can be specified
 374 for semi-stable and anti-stable systems by $CCP = X_0 \cap \mathcal{A}_0$ [16]. Using (2) we have,
 375 $X_0 = \bigcup_{t \geq 0} \{x : x = -\int_0^t e^{-A\tau} b u(\tau) d\tau, u(\tau) \in U\}$ and from (3), $\mathcal{A}_0 = \bigcup_{t \geq 0} \{x : x =$
 376 $\int_0^t e^{A\tau} b u(\tau) d\tau, u(\tau) \in U\}$.

377 **Theorem 13.** *If for system (1), $A = \text{diag}(A_1, A_2)$, with $A_1 \in \mathbb{R}^{(n-m) \times (n-m)}$ anti-stable*
 378 *($\lambda(A_1) > 0$) and $A_2 \in \mathbb{R}^{m \times m}$ semi-stable ($\lambda(A_2) \leq 0$), b is partitioned accordingly as*
 379 $b = \begin{bmatrix} b_1^T & b_2^T \end{bmatrix}^T$ *and origin lies in CCP , then $CCP = X_0^1 \times \mathcal{A}_0^2$ where X_0^1 is the null*
 380 *controllable set for anti-stable system $\dot{x}_1 = A_1 x_1 + b_1 u$ and \mathcal{A}_0^2 is attainable set for the*
 381 *stable system $\dot{x}_2 = A_2 x_2 + b_2 u$.*

382 *Proof.* We have $X_0 = X_0^1 \times \mathbb{R}^m$ and similarly $\mathcal{A}_0 = \mathbb{R}^{(n-m)} \times \mathcal{A}_0^2$ [20]. Therefore,
 383 $CCP = X_0 \cap \mathcal{A}_0 = (X_0^1 \times \mathbb{R}^m) \cap (\mathbb{R}^{(n-m)} \times \mathcal{A}_0^2) = (X_0^1 \cap \mathbb{R}^{(n-m)}) \times (\mathbb{R}^m \cap \mathcal{A}_0^2) = X_0^1 \times \mathcal{A}_0^2$. \square

384 Thus, to check whether given $x = [x_1 \ x_2]^T \in CCP$, we independently check
 385 whether $x_1 \in X_0^1$ and $x_2 \in \mathcal{A}_0^2$. But, the attainable set \mathcal{A}_0^2 of $\dot{x}_2 = A_2 x_2 + b_2 u$ is same

386 as the reachability set of $\dot{x}_2 = -A_2x_2 + b_2u$. Hence, it is enough to compute the null-
 387 controllable region X_0 just for anti-stable systems to characterize CCP for any given
 388 system. Next we characterize the reachable set X_p for a point $p \in CCP$. The following
 389 lemma from [16] can be used directly.

390 **Lemma 14.** $X_p = X_0$ if and only if $p \in \mathcal{A}_0 \cap X_0 = CCP$.

391 From this lemma, it is clear that the semi-algebraic characterization of X_p for any
 392 point $p \in CCP$ is same as that of null-controllability region X_0 of the given system. As
 393 mentioned above, X_0 can be computed using the method proposed in [5, 6].

394 8. Conclusion

395 In this article, we extend previous synthesis results to the case of non-zero target
 396 states and relax the assumption on eigenvalues to include zero eigenvalue. In practice, the
 397 switching feedback law drives the system to a some neighborhood of p , in near optimal
 398 time. The presence of limit cycles, even for time optimal transfer, is an interesting
 399 feature of this development. A characterization of the target points for which limit cycle
 400 exists is provided. Properties of the limit cycle for different target points are studied.
 401 The proposed method is currently limited to controllable diagonalizable systems with
 402 rational eigenvalues. Relaxing some of these assumptions is the subject of current and
 403 future research.

404 References

- 405 [1] B. Buchberger, Gröbner Bases and Systems Theory, Multidimensional Syst. Signal Process. 12 (3-4)
 406 (2001) 223–251.
 407 [2] Z. Lin, L. Xu, N. Bose, A Tutorial on Gröbner Bases With Applications in Signals and Systems,
 408 IEEE Transactions on Circuits and Systems I: Regular Papers, 55 (1) (2008) 445–461.
 409 [3] H. Shin, S. Lall, Decentralized control via groebner bases and variable elimination, IEEE Transac-
 410 tions on Automatic Control, 57 (4) (2012) 1030–1035.
 411 [4] L. Pontryagin, V. Boltyanskii, R. Gamkrelidze, E. Mischenko, The Mathematical Theory of Optimal
 412 Control, Interscience Publishers, 1962.
 413 [5] D. Patil, D. Chakraborty, Switching surfaces and null-controllable region of a class of LTI systems
 414 using Groebner basis, in: IEEE 51st Annual Conference on Decision and Control (CDC), 2012,
 415 1279–1284, Dec. 2012.
 416 [6] D. U. Patil, D. Chakraborty, Computation of Time Optimal Feedback Control Using Groebner
 417 Basis, IEEE Trans. Automat. Contr. 59 (8) (2014) 2271–2276.
 418 [7] J. Liang, R. Fullmer, Y. Q. Chen, Time-optimal magnetic attitude control for small spacecraft, in:
 419 43rd IEEE Conference on Decision and Control, 2004. CDC., vol. 1, 255 – 260 Vol.1, 2004.
 420 [8] E. Sontag, H. Sussmann, Time-optimal control of manipulators, in: Proceedings of IEEE Interna-
 421 tional Conference on Robotics and Automation. 1986, vol. 3, IEEE, 1692–1697, 1986.

- 422 [9] S. H. Lim, T. Furukawa, G. Dissanayake, H. Durrant-Whyte, A time-optimal control strategy for
423 pursuit-evasion games problems, in: Proceedings of IEEE International Conference on Robotics and
424 Automation. 2004, vol. 4, 3962 – 3967 Vol.4, 2004.
- 425 [10] D. U. Patil, A. K. Mulla, D. Chakraborty, H. Pillai, Gröbner Basis Computation of Feedback
426 Control for Time Optimal State Transfer, in: Proceedings of IEEE 52nd Annual Conference on
427 Decision and Control (CDC), 3243–3248, 2013.
- 428 [11] D. Stansbery, J. Cloutier, Position and attitude control of a spacecraft using the state-dependent
429 Riccati equation technique, in: Proceedings of the American Control Conference, 2000., vol. 3, 1867
430 –1871 vol.3, 2000.
- 431 [12] O. Hajek, Terminal manifolds and switching locus, Theory of Computing Systems 6 (3) (1971)
432 289–301.
- 433 [13] D. S. .Yeung, Time-Optimal Feedback Control, Journal of Optimization theory and applications
434 21 (1) (1977) 71–82.
- 435 [14] M. Fashoro, Geometric properties of constrained linear systems, in: Twenty-Third Southeastern
436 Symposium on System Theory, 1991. Proceedings., 306 –318, 1991.
- 437 [15] M. Fashoro, O. Hajek, K. Loparo, Controllability properties of constrained linear systems, Journal
438 of Optimization Theory and Applications 73 (1992) 329–346.
- 439 [16] M. Fashoro, O. Hajek, K. Loparo, Reachability properties of constrained linear systems, Journal of
440 Optimization Theory and Applications 73 (1992) 169–195.
- 441 [17] D. Cox, J. Little, D. O’Shea, Ideals, Varieties and Algorithms: An Introduction to Computational
442 Algebraic Geometry and Commutative Algebra, Springer, 2007.
- 443 [18] W. Decker, G.-M. Greuel, G. Pfister, H. Schönemann, SINGULAR 3-1-5 — A computer algebra
444 system for polynomial computations [Http://www.singular.uni-kl.de](http://www.singular.uni-kl.de).
- 445 [19] V. I. Utkin, Sliding modes in control and optimization, vol. 116, Springer-Verlag Berlin, 1992.
- 446 [20] T. Hu, Z. Lin, Control Systems with Actuator Saturation: Analysis and Design, Birkhäuser, 2001.