We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

6,900
Open access books available

186,000
International authors and editors

200M
Downloads

Our authors are among the

154
Countries delivered to

TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

8

Using Subsets Sequence to Approach the Maximal Terminal Region for MPC

Yafeng Wang[1,2], Fuchun Sun[2], Youan Zhang[1],
Huaping Liu[2] and Haibo Min[2]
[1]*Department of Control Engineering, Naval Aeronautical Engineering University, Yantai,*
[2]*Department of Computer Science and Technology, Tsinghua University, Beijing, China*

1. Introduction

Due to the ability to handle control and state constraints, MPC has become quite popular recently. In order to guarantee the stability of MPC, a terminal constraint and a terminal cost are added to the on-line optimization problem such that the terminal region is a positively invariant set for the system and the terminal cost is an associated Lyapunov function [1, 9].
As we know, the domain of attraction of MPC can be enlarged by increasing the prediction horizon, but it is at the expense of a greater computational burden. In [2], a prediction horizon larger than the control horizon was considered and the domain of attraction was enlarged. On the other hand, the domain of attraction can be enlarged by enlarging the terminal region. In [3], an ellipsoidal set included in the stabilizable region of using linear feedback controller served as the terminal region. In [4], a polytopic set was adopted. In [5], a saturated local control law was used to enlarge the terminal region. In [6], SVM was employed to estimate the stabilizable region of using linear feedback controller and the estimated stabilizable region was used as the terminal region. The method in [6] enlarged the terminal region dramatically. In [7], it was proved that, for the MPC without terminal constraint, the terminal region can be enlarged by weighting the terminal cost. In [8], the enlargement of the domain of attraction was obtained by employing a contractive terminal constraint. In [9], the domain of attraction was enlarged by the inclusion of an appropriate set of slacked terminal constraints into the control problem.
In this paper, the domain of attraction is enlarged by enlarging the terminal region. A novel method is proposed to achive a large terminal region. First, the sufficient conditions to guarantee the stability of MPC are presented and the maximal terminal region satisfying these conditions is defined. Then, given the terminal cost and an initial subset of the maximal terminal region, a subsets sequence is obtained by using one-step set expansion iteratively. It is proved that, when the iteration time goes to infinity, this subsets sequence will converge to the maximal terminal region. Finally, the subsets in this sequence are separated from the state space one by one by exploiting SVM classifier (see [10,11] for details of SVM).

2. Model predictive control

Consider the discrete-time system as follows

$$x_{k+1} = f(x_k, u_k) \tag{1}$$

where $x_k \in R^n$, $u_k \in R^m$ are the state and the input of the system at the sampling time k respectively. $x_{k+1} \in R^n$ is the successor state and the mapping $f: R^{n+m} \mapsto R^n$ satisfying $f(\mathbf{0},\mathbf{0}) = \mathbf{0}$ is known. The system is subject to constraints on both state and control action. They are given by $x_k \in X$, $u_k \in U$, where X is a closed and bounded set, U is a compact set. Both of them contain the origin.

The on-line optimization problem of MPC at the sample time k, denoted by $P_N(x_k)$, is stated as

$$\begin{aligned} \min_{u(i,x_k)\in U} J_N(\boldsymbol{u}, x_k) &= \sum_{i=0}^{N-1} q\big(x(i,x_k), u(i,x_k)\big) + F\big(x(N,x_k)\big) \\ s.t.\ \ x(i+1,x_k) &= f\big(x(i,x_k), u(i,x_k)\big) \\ x(i+1,x_k) &\in X, u(i,x_k) \in U, x(N,x_k) \in X_f \end{aligned} \tag{2}$$

where $x(0,x_k) = x_k$ is the state at the sample time k, $q(x,u)$ denotes the stage cost and it is positive definite, N is the prediction horizon, X_f denotes the terminal region and it is closed and satisfies $\mathbf{0} \in X_f \subseteq X$, $F(\cdot)$ satisfying $F(\mathbf{0}) = 0$ is the terminal cost and it is continuous and positive definite.

Consider an assumption as follows.

Assumption 1. For the terminal region and the terminal cost, the following two conditions are satisfied [1]:

(C1) $F(\cdot)$ is a Lyapunov function. For any $x \in X_f$, there exists

$$F(x) \geq \min_{u\in U}\{q(x,u) + F(f(x,u))\}.$$

(C2) X_f is a positively invariant set. For any $x \in X_f$, by using the optimal control resulting from the minimization problem showed in (C1), denoted by u_{opt}, we have $f(x, u_{opt}) \in X_f$.

Let $J_N^*(x_k)$ be the minimum of $P_N(x_k)$ and $\boldsymbol{u}_{\boldsymbol{N}}^*(x_k) = \{u_{\boldsymbol{N}}^*(0,x_k), \cdots, u_{\boldsymbol{N}}^*(N-1,x_k)\}$ be the optimal control trajectory. The control strategy of MPC is that, at the sample time k, $u_{\boldsymbol{N}}^*(0,x_k)$ is inputted into the real system and at the sample time $k+1$, the control inputted into the system is not $u_{\boldsymbol{N}}^*(1,x_k)$ but the first element of the optimal control trajectory resulting from the similar on-line optimization problem. At the sample time $k+1$, the state is $x_{k+1} = f(x_k, u_{\boldsymbol{N}}^*(0,x_k))$ and the on-line optimization problem, denoted by $P_N(x_{k+1})$, is same as (2) except that x_k is replaced by x_{k+1}. Similarly, let $J_N^*(x_{k+1})$ be the minimum of $P_N(x_{k+1})$ and $\boldsymbol{u}_{\boldsymbol{N}}^*(x_{k+1}) = \{u_{\boldsymbol{N}}^*(0,x_{k+1}), \cdots, u_{\boldsymbol{N}}^*(N-1,x_{k+1})\}$ be the optimal control trajectory. The control inputted into the system at the sample time $k+1$ is $u_{\boldsymbol{N}}^*(0,x_{k+1})$. So, the control law of MPC can be stated as $u_{RH}(x_k) = u_N^*(0,x_k), k = 0,1,2,\cdots,\infty$.

The closed-loop stability of the controlled system is showed in lemma 1.

Lemma 1. For any $x_0 \in X$, if x_0 satisfies $x_N^*(N,x_0) \in X_f$ and assumption 1 is satisfied, it is guaranteed that, x_0 will be steered to $\mathbf{0}$ by using the control law of MPC.

The proof can be found in [1].

Proof. The proof of lemma 1 is composed of two parts: the existence of feasible solution; the monotonicity of $J_N^*(\cdot)$.

Part 1. At the sample time 1, $x_1 = x^*(1,x_0) = f\left(x_0, u^*(0,x_0)\right)$ is obtained by inputting $u^*(0,x_0)$ into the system, where $u^*(0,x_0)$ denotes the first element of the optimal solution of $P_N(x_0)$. It is obvious that, $\boldsymbol{u}(x_1) = \left\{u^*(1,x_0),\cdots,u^*(N-1,x_0),u_{opt}\left(x^*(N,x_0)\right)\right\}$ is a feasible solution of $P_N(x_1)$ since $x^*(N,x_0) \in X_f$ and $f\left(x^*(N,x_0),u_{opt}\left(x^*(N,x_0)\right)\right) \in X_f$ as assumption 1 shows.

Part 2. When $\boldsymbol{u}(x_1)$ is used, we have

$$\begin{aligned} & J_N\left(\boldsymbol{u}(x_1),x_1\right) - J_N^*(x_0) \\ &= q\left(x^*(N,x_0),u_{opt}\left(x^*(N,x_0)\right)\right) + F\left(f\left(x^*(N,x_0),u_{opt}\left(x^*(N,x_0)\right)\right)\right) \\ &\quad - q\left(x^*(0,x_0),u^*(0,x_0)\right) - F\left(x^*(N,x_0)\right) \\ &\le -q\left(x^*(0,x_0),u^*(0,x_0)\right) \\ &\le 0 \end{aligned}$$

Since $J_N^*(x_1) \le J_N\left(\boldsymbol{u}(x_1),x_1\right)$, it follows that, $J_N^*(x_1) - J_N^*(x_0) \le 0$.

Endproof.

3. Using subsets sequence to approach the maximal terminal region

Using SVM classifier to estimate the terminal region is not a new technology. In [6], a large terminal region was achieved by using SVM classifier. However, the method in [6] is somewhat conservative. The reason is that, the obtained terminal region actually is the stabilizable region of using a predetermined linear feedback controller.

In this section, a novel method of computing a terminal region is proposed. Given the terminal cost and a subset of the maximal terminal region, a subsets sequence is constructed by using one-step set expansion iteratively and SVM is employed to estimate each subset in this sequence. When some conditions are satisfied, the iteration ends and the last subset is adopted to serve as the terminal region.

3.1 The construction of subsets sequence

Consider an assumption as follows.

Assumption 2. A terminal cost is known.

If the stage cost is a quadratic function as $q(x,u) = x^T Q x + u^T R u$ in which Q, R are positive definite, a method of computing a terminal cost for continuous-time system can be found in [3]. In this paper, the method in [3] is extended to discrete-time system. Consider the linearization of the system (1) at the origin

$$x_{k+1} = A_d x_k + B_d u_k$$

with $A_d = (\partial f / \partial x)(0,0)$ and $B_d = (\partial f / \partial u)(0,0)$.

A terminal cost can be obtained through the following procedure:

Step 1. Solving the Riccati equation to get G_0,

$$G_0 = A_d^T G_0 A_d - \left(A_d^T G_0 B_d\right)\left(B_d^T G_0 B_d + R\right)^{-1}\left(B_d^T G_0 A_d\right) + Q$$

Step 2. Getting a locally stabilizing linear state feedback gain K,

$$K = -\left(B_d^T G_0 B_d + R\right)^{-1}\left(B_d^T G_0 A_d\right)$$

Step 3. Computing G_K by solving the following Riccati equation,

$$\left(\alpha A_K\right)^T G_K \left(\alpha A_K\right) - G_K = -Q_K$$

where $A_K = A_d + B_d K$, $Q_K = Q + K^T R K$, and $\alpha \in [1, +\infty)$ is an adjustable parameter satisfying $\alpha \left|\lambda_{\max}(A_K)\right| < 1$. Then, $F(x) = x^T G_K x$ can serve as a terminal cost.
Given $F(\cdot)$ and from conditions (C1,C2), the terminal region X_f can be defined as

$$X_f := \left\{x \in X \mid F(x) \geq F_{X_f}^*(x)\right\} \tag{3}$$

where $F_{X_f}^*(x)$ is the minimum of the following optimization problem

$$\begin{aligned} &\min_{u \in U} F_{X_f}(x) = q(x,u) + F\left(f(x,u)\right) \\ &s.t. \qquad f(x,u) \in X_f \end{aligned} \tag{4}$$

Remark 1. The construction of X_f has two meanings: (I) the optimization problem (4) has feasible solution, that is to say, $\exists u \in U$, s.t. $f(x,u) \in X_f$; (II) the minimum of the optimization problem satisfies that $F_{X_f}^*(x) \leq F(x)$.
Remark 2. From the definition of X_f, it is obvious that, the terminal region is essentially a positively invariant set of using the optimal control resulting from the optimization problem (4) when $F(\cdot)$ is given.
Remark 3. In [3,4,6], the linear feedback control is attached to the construction of X_f and X_f is the stabilizable region of using the linear feedback controller. In [5], a saturated local control law was used. But, in this paper, there is no explicit control attached to the definition of X_f. So, the requirement on X_f is lower than that in [3-6] while guaranting the stability of the controlled system.
From the definition of X_f, it can not be determined whether a state point belongs to X_f. The difficulty lies in that, the X_f itself acts as the constraint in the optimization problem (4). To avoid this problem, the method of using one-step set expansion iteratively is adopted. Define $X_{f,\max}$ as the largest terminal region and consider an assumption.

Assumption 2. A subset of $X_{f,\max}$, denoted by X_f^0 and containing the origin, is known.

Assumption 3. X_f^0 is a positively invariant set, that is to say, for any $x \in X_f^0$, $\exists u \in U$, s.t. $F(x) \geq q(x,u) + F\left(f(x,u)\right)$ and $f(x,u) \in X_f^0$.

Given X_f^0, another subset of $X_{f,\max}$, denoted by X_f^1, can be constructed as

$$X_f^1 := \left\{ x \in X \mid F(x) \geq F_{X_f^0}^*(x) \right\} \tag{5}$$

where $F_{X_f^0}^*(x)$ is the minimum of

$$\begin{aligned} &\min_{u \in U} F_{X_f^0}(x) = q(x,u) + F\left(f(x,u)\right) \\ &s.t. \quad f(x,u) \in X_f^0 \end{aligned} \tag{6}$$

As mentioned in remark 1, the construction of X_f^1 contains two meanings: (I) for any $x \in X_f^1$, $\exists u \in U$, s.t. $f(x,u) \in X_f^0$; (II) the minimum of (6) satisfies $F_{X_f^0}^*(x) \leq F(x)$. The constructions of X_f^j in sequel have the similar meanings.

Lemma 2. If assumption 3 is satisfied, there is $X_f^0 \subseteq X_f^1$.

Proof. If assumption 3 is satisfied, it is obvious that, for any $x \in X_f^0$, $\exists u \in U$, s.t. $F(x) \geq q(x,u) + F\left(f(x,u)\right)$ and $f(x,u) \in X_f^0$. It follows that, $F(x) \geq F_{X_f^0}^*(x)$. From the construction of X_f^1, we can know $x \in X_f^1$, namely, $X_f^0 \subseteq X_f^1$.
Endproof.

Remark 4. From the construction of X_f^1, it is obvious that, if assumption 3 is satisfied, X_f^1 is a positively invariant set. We know that, for any $x \in X_f^1$, $\exists u \in U$, s.t. $F(x) \geq q(x,u) + F\left(f(x,u)\right)$ and $f(x,u) \in X_f^0$. Because of $X_f^0 \subseteq X_f^1$ as showed in lemma 2, we have $f(x,u) \in X_f^1$.

Similarly, by replacing X_f^0 with X_f^1 in the constraint of (6), another subset, denoted by X_f^2, can be obtained as follows

$$X_f^2 := \left\{ x \in X \mid F(x) \geq F_{X_f^1}^*(x) \right\} \tag{7}$$

where $F_{X_f^1}^*(x)$ is the minimum of

$$\begin{aligned} &\min_{u \in U} F_{X_f^1}(x) = q(x,u) + F\left(f(x,u)\right) \\ &s.t. \quad f(x,u) \in X_f^1 \end{aligned} \tag{8}$$

Repeatedly, X_f^j, $j = 3,4,\cdots,\infty$ can be constructed as

$$X_f^j := \left\{ x \in X \mid F(x) \geq F_{X_f^{j-1}}^*(x) \right\} \tag{9}$$

where $F_{X_f^{j-1}}^*(x)$ is the minimum of

$$\begin{aligned} &\min_{u \in U} F_{X_f^{j-1}}(x) = q(x,u) + F\left(f(x,u)\right) \\ &s.t. \quad f(x,u) \in X_f^{j-1} \end{aligned} \tag{10}$$

This method of constructing X_f^j given X_f^{j-1} is defined as one-step set expansion in this paper. By employing it iteratively, a subsets sequence of largest terminal region, denoted by $\left\{X_f^j\right\}$, $j=1,2,\cdots,\infty$, can be achived.

Remark 5. Similar with lemma 2 and remark 4, any subset in this sequence is positively invariant and any two neighbouring subsets satisfy $X_f^{j-1}\subseteq X_f^j$.

As j increases, $\left\{X_f^j\right\}$ will converge to a set, denoted by $X_f^{+\infty}$. Theorem 1 will show that, $X_f^{+\infty}$ is equal to the largest terminal region.

Theorem 1. *If assumption 2 and assumption 3 are satisfied, for X_f^j constructed in (9) and (10), when j goes to infinity, $\left\{X_f^j\right\}$ will converge to $X_{f,\max}$.*

Proof. This theorem is proved by contradiction.

(A) Assume that, there exists a set which is denoted by X_{spo} satisfying $X_{spo}\subset X_{f,\max}$ and $X_f^j\to X_{spo}$ when $j\to+\infty$. From remark 5, we can know $X_f^0\subseteq X_{spo}$. It is obvious that $\mathbf{0}\in X_{spo}$ because of $\mathbf{0}\in X_f^0$ as showed in assumption 2. It follows that, $\mathbf{0}\notin X_{f,\max}\setminus X_{spo}$ and for any $x\in X_{f,\max}\setminus X_{spo}$, we have $F(x)>0$ since $F(\cdot)$ is positive definite. Define ξ as the infimum of $\left\{F(x)\,|\,x\in X_{f,\max}\setminus X_{spo}\right\}$, it is satisfied that, $\xi>0$.

From the construction of X_f^j, we know that, for any $x_0\in X_{f,\max}\setminus X_{spo}$, there exists no such a $u\in U$ satisfying $F(x_0)\geq q(x_0,u)+F\left(f(x_0,u)\right)$ and $f(x_0,u)\in X_{spo}$ because of $X_{spo}\subset X_{f,\max}$. However, from (C1) and (C2), we know that, $\exists u(x_0)\in U$, s.t. $F(x_0)\geq q\left(x_0,u(x_0)\right)+F(x_1)$ and $x_1\in X_{f,\max}$, where $x_1=f\left(x_0,u(x_0)\right)$. It is obvious that, $x_1\notin X_{spo}$. So we have, $x_1\in X_{f,\max}\setminus X_{spo}$. Similarly, we can know, $\exists u(x_1)\in U$, s.t. $F(x_1)\geq q\left(x_1,u(x_1)\right)+F(x_2)$ and $x_2\in X_{f,\max}\setminus X_{spo}$, where $x_2=f\left(x_1,u(x_1)\right)$, since $x_1\in X_{f,\max}\setminus X_{spo}$.

Repeatly, for $x_i\in X_{f,\max}\setminus X_{spo}$, $\exists u(x_i)\in U$, s.t. $F(x_i)\geq q\left(x_i,u(x_i)\right)+F(x_{i+1})$ and $x_{i+1}\in X_{f,\max}\setminus X_{spo}$, where $x_{i+1}=f\left(x_i,u(x_i)\right)$, $i=2,\cdots,\infty$. It is clear that, $F(x_i)\to 0$ when $i\to\infty$. We know that, for the infimum of $\left\{F(x)\,|\,x\in X_{f,\max}\setminus X_{spo}\right\}$, defined as ξ, there is a positive real number δ satisfing $0<\delta<\xi$. Since $F(x_i)\to 0$ when $i\to\infty$, $\exists N_\delta>0$, s.t. for any $i\geq N_\delta$, we have $F(x_i)<\delta$. Obviously, this is contradicted with that ξ is the infimum of $\left\{F(x)\,|\,x\in X_{f,\max}\setminus X_{spo}\right\}$.

(B) Similarly, assume that, there exists a X_{spo} satisfying $X_{spo}\supset X_{f,\max}$ and $X_f^j\to X_{spo}$ when $j\to+\infty$. For any $x\in X_{spo}$, we have that $F(x)\geq\min\limits_{u\in U}\left\{q(x,u)+F\left(f(x,u)\right)\right\}$ and $f(x,u)\in X_{spo}$. Obviously, this is contradicted with that $X_{f,\max}$ is the largest one satisfying (C1) and (C2).

Endproof.

Remark 6. In this paper, the largest terminal region means the positively invariant set satisfying conditions (C1) and (C2). But, (C1) and (C2) are sufficient conditions to guarantee the stability of the controlled system, not the necessary conditions. There may be a set larger than $X_{f,\max}$ and the stability of the controlled system can be guaranteed by using this set as the terminal region.

Remark 7. In the calculation of $X_{f,\max}$, it is impossible to keep iteration computation until $j\to+\infty$. When the iteration time goes to $j=E$ (E is a positive integer), if X_f^E is equal to X_f^{E-1} in principle, it can be deemed that $\left\{X_f^j\right\}$ converges to X_f^E in rough. Hence, X_f^E can be taken as the terminal region and it is a good approximation to $X_{f,\max}$.

Remark 8. If the iteration time does not go to infinity, the obtained set may be just a large positively invariant subset of $X_{f,\max}$. This has no effect on the stability of the controlled

system. The only negative influence is that its corresponding domain of attraction is smaller than that corresponding to $X_{f,\max}$.

Untill now, it seems that we can choose any X_f^j in the subsets sequence as the terminal region. This is infeasible. Since X_f^j is not described in explicit expression, it can not serve as the terminal constraint in the optimization problem (2) directly. Then, an estimated one described in explicit expression is needed. Due to the strong optimizing ability of SVM, SVM is exploited to separate each X_f^j from the state space.

3.2 Support vector machine

SVM is the youngest part in the statistical learning theory. It is an effective approach for pattern recognition. In SVM approach, the main aim is to obtain a function, which determines the decision boundary or hyperplane. This hyperplane optimally separates two classes of input data points.

Take the example of separating X into A and $X \setminus A$. For each $x_i \in A$, an additional variable $y_i = +1$ is introduced. Similarly, for each $x_i \in X \setminus A$, $y_i = -1$ is introduced. Define $I^+ := \{i : y_i = +1\}$ and $I^- := \{i : y_i = -1\}$, SVM will find a separating hyperplane, denoted by $O(x) := w \cdot \phi(x_i) + b = 0$, between A and $X \setminus A$. Therefore, A can be estimated as $\hat{A} = \{x \in X \mid O(x) \geq 0\}$, where $O(x)$ is determined by solving the following problem:

$$\begin{aligned} \min_{\alpha} \quad & \frac{1}{2}\sum_i \sum_j \alpha_i \alpha_j y_i y_j ker(x_i, x_j) - \sum_i \alpha_i \\ \text{s.t.} \quad & \sum_i \alpha_i y_i = 0 \\ & 0 \leq \alpha_i \leq C, \ \forall i \in I^+; \ \alpha_i \geq 0, \forall i \in I^- \end{aligned} \tag{11}$$

where $ker(\cdot,\cdot)$ denotes the kernel function and the Gaussian kernel as follows is adopted in this paper:

$$ker(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \tag{12}$$

with σ being the positive Gaussian kernel width.

When $\{\alpha_i\}$ are computed out, some support vectors are chosen from $\{x_i\}$ and the optimal hyperplane can be determined with these support vectors and their relevant weights. Denote P_s as the number of support vectors and X_s as the support vectors set, the optimal hyperplane is described as:

$$O(x) = \sum_{i=1}^{P_s} w_i \cdot ker(x_i, x) + b \tag{13}$$

where $x_i \in X_s$ is the support vector and $w_i = \alpha_i y_i$ satifying $\sum_{i=1}^{P_s} w_i = 0$ is the relevant weight. There are many software packages of SVM available on internet. They can be downloaded and used directly. To save space, it is not introduced in detail in this paper. For more details, please refer to [10] and [11].

3.3 Estimating the subset by employing SVM

From subsection 3.2, we know that, SVM find a separating hyperplane between $\{x_i \mid i \in I^+\}$ and $\{x_i \mid i \in I^-\}$.This hyperplane is used to separate X into A and $X \setminus A$. All of $\{x_i\}$ and their relevant $\{y_i\}$ compose a set, named the training points set. This subsection will show how to achieve the training points set when estimating X_f^j and how to determine X_f^j when the separating hyperplane is known.

Firstly, choose arbitrary points $x_i \in X$, $i = 1,2,...,P$ (P is the number of training points); then, assign y_i to each x_i by implementing the following procedure:

IF (I) the following optimization problem has feasible solution

$$\min_{u \in U} F_{X_f^j}(x_i) = q(x_i, u) + F\left(f(x_i, u)\right)$$
$$s.t. \qquad f(x_i, u) \in \hat{X}_f^{j-1} \qquad .$$

(When $j = 1$, $\hat{X}_f^0 = X_f^0$.)

(II) its minimum satisfies

$$F(x_i) \geq F_{X_f^j}^*(x_i) .$$

THEN $y_i = +1$

ELSE $y_i = -1$

ENDIF.

By implementing this procedure for every x_i, each y_i is known. Input $\{x_i\}$ and $\{y_i\}$ into SVM classifier, an optimal hyperplane $O^j(x) = 0$ will be obtained. Therefore, the estimated set of X_f^j can be achieved as $\hat{X}_f^j = \left\{x \in X \mid O^j(x) \geq 0\right\}$.

When $\hat{X}_f^j$ is known, the training points for separating X_f^{j+1} from X can be computed by the similar procedure. By inputting them into SVM classifier, a hyperplane $O^{j+1}(x) = 0$ and an estimated set of X_f^{j+1}, denoted by $\hat{X}_f^{j+1} = \left\{x \in X \mid O^{j+1}(x) \geq 0\right\}$ will be obtained. Repeatedly, $\left\{O^j(x)\right\}, j = 1,2,\cdots,\infty$ and $\left\{\hat{X}_f^j\right\}$ can be be achieved by the similar technology.

4. Estimating the terminal region

Section 3 showed how to achieve the subsets sequence by employing SVM. Theoretically, the larger the iteration time j, the higher the precision of $\hat{X}_f^j$ approaching to $X_{f,\max}$. But, it is impossible to keep computation until $j \to +\infty$. To avoid this problem, the iteration should be ended when some conditions are satisfied.

When $j = E$, if it is satisfied that, for $x_i \in X_{s,E-1}$, $i = 1,2,\cdots,P_{s,E-1}$, there exists

$$\sum_{i=1}^{P_{s,E-1}} \left\| O^E(x_i) - O^{E-1}(x_i) \right\| \leq \varepsilon P_{s,E-1}, \tag{14}$$

it can be deemed that $\hat{X}_f^E$ is equal to $\hat{X}_f^{E-1}$ in principle and $\hat{X}_f^j$ converges to $\hat{X}_f^E$. In (14), $X_{s,E-1}$ is the support vectors set at $j=E-1$, $P_{s,E-1}$ is the number of support vectors and ε is a tunable threshold. The smaller ε is, the higher the precision of $\hat{X}_f^E$ approximating to $X_{f,\max}$ is. Finally, $\hat{X}_f^E$ is used to serve as the terminal region.

Remark 9. Here, we used the information that, in SVM classifier, the hyperplanes are only determined on the support vectors.

Now, the concrete algorithm of estimating the largest terminal region is displayed as follows.

Step 4. Step 1 Set the number of training points P used in SVM and the tunable threshold ε.

Step 5. Step 2 For $j=1,2,\cdots,\infty$, use SVM to achieve the optimal hyperplane $O^j(x)=0$ and the estimated set of X_f^j, denoted by $\hat{X}_f^j$.

Substep 1. Choose arbitrary points $x_i \in X$, $i=1,2,...,P$.

Substep 2. Assign y_i to each x_i by implementing the procedure in subsection 3.3.

Substep 3. Input $\{x_i, y_i\}$ into the SVM. An optimal hyperplane $O^j(x)=0$ will be obtained and X_f^j can be approximated by $\hat{X}_f^j = \{x \in X \mid O^j(x) \geq 0\}$, where

$$O^j(x) = \sum_{i=1}^{P_{s,j}} w_i \cdot ker(x_i, x) + b_j$$

with $P_{s,j}$ denoting the number of support vectors, x_i being the support vector, w_i denoting its relevant weight and b_j denoting the classifier threshold.

Step 6. Step 3 Check the iteration status. When $j=E$, if inequality (14) is satisfied, end iteration and take $\hat{X}_f^E$ as the largest terminal region.

Remark 10. It is obvious that, $\hat{X}_f^j$ is achieved one by one. Namely, $\hat{X}_f^j$ can only be achieved when $\hat{X}_f^{j-1}$ is known.

5. Simulation experiment

The model is a discrete-time realization of the continuous-time system used in [3, 6]:

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix} = \begin{bmatrix} 1 & T \\ T & 1 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} + \begin{bmatrix} T\mu \\ T\mu \end{bmatrix} u(k) + \begin{bmatrix} T(1-\mu) & 0 \\ 0 & -4T(1-\mu) \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} u(k)$$

where $\mu = 0.5$, $T = 0.1s$, and the state constraint and control constraint are $X = \{x \mid \|x\|_1 \leq 4\}$, $U = \{u \mid |u| \leq 2\}$, respectively.

The stage cost is $q(x,u) = x^T Q x + u^T R u$ where $Q = 0.5I$ and $R = 1$. The terminal cost is chosen as $F(x) = x^T G x$ where $G = [1107.356 \quad 857.231; 857.231 \quad 1107.356]$ and X_f^0 is given as the terminal region in [3] which is

$$X_f^0 = \left\{ x \in X \mid x^T \begin{bmatrix} 16.5926 & 11.5926 \\ 11.5926 & 16.5926 \end{bmatrix} x \le 0.7 \right\}.$$

To estimate each X_f^j, 4000 training points are generated. Set $\varepsilon = 2.5$, when $j = 22$, there exists

$$\sum_{i=1}^{P_{s,21}} \left\| O^{22}(x_i) - O^{21}(x_i) \right\| \le \varepsilon P_{s,21},$$

where $x_i \in X_{s,21}$, $X_{s,21}$ is the support vectors set and $P_{s,21}$ is the number of support vectors at $j = 21$. Then, it is deemed that, $\hat{X}_f^{22}$ is equal to $\hat{X}_f^{21}$ in principle and $\hat{X}_f^{22}$ can be taken as the final estimation of $X_{f,\max}$. Figure 1 shows the approximation process of $X_{f,\max}$.

In figure 1, the blue ellipsoid is the terminal region in [3], which serves as X_f^0 in the estimation of $X_{f,\max}$ in this paper. The regions surrounded by black solid lines are $\left\{ \hat{X}_f^j \right\}, j = 1,2,\cdots 22$ in which the smallest one is $\hat{X}_f^1$, the largest one is $\hat{X}_f^{22}$ and the regions between them are $\left\{ \hat{X}_f^j \right\}, j = 2,3,\cdots 21$ satisfying $\hat{X}_f^{j-1} \subseteq \hat{X}_f^j$. The time cost of employing SVM to estimate each $\hat{X}_f^j$ is about 44 minutes and the total time cost of computing the final estimation of $X_{f,\max}$, namely, $\hat{X}_f^{22}$ is about 16 hours.

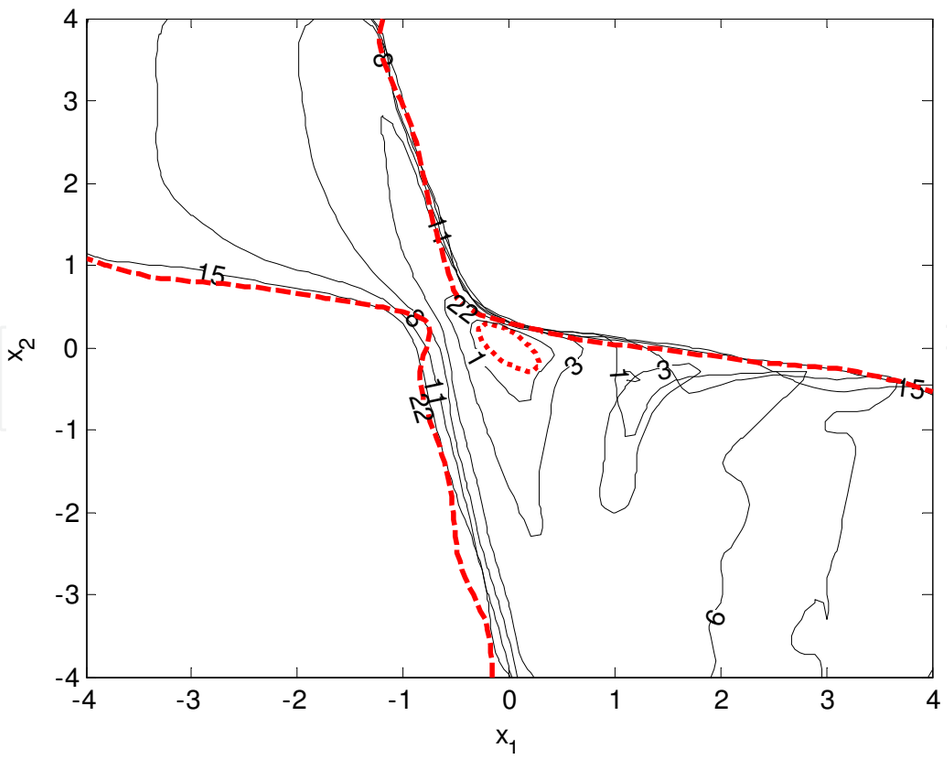


Fig. 1. The approximation process

Set the prediction horizon as $N = 3$, some points in the region of attraction (this example is very exceptional, the region of attraction is coincident with the terminal region in rough. Therefore, these points are selected from the terminal region) are selected and their closed-loop trajectories are showed in Figure 2.

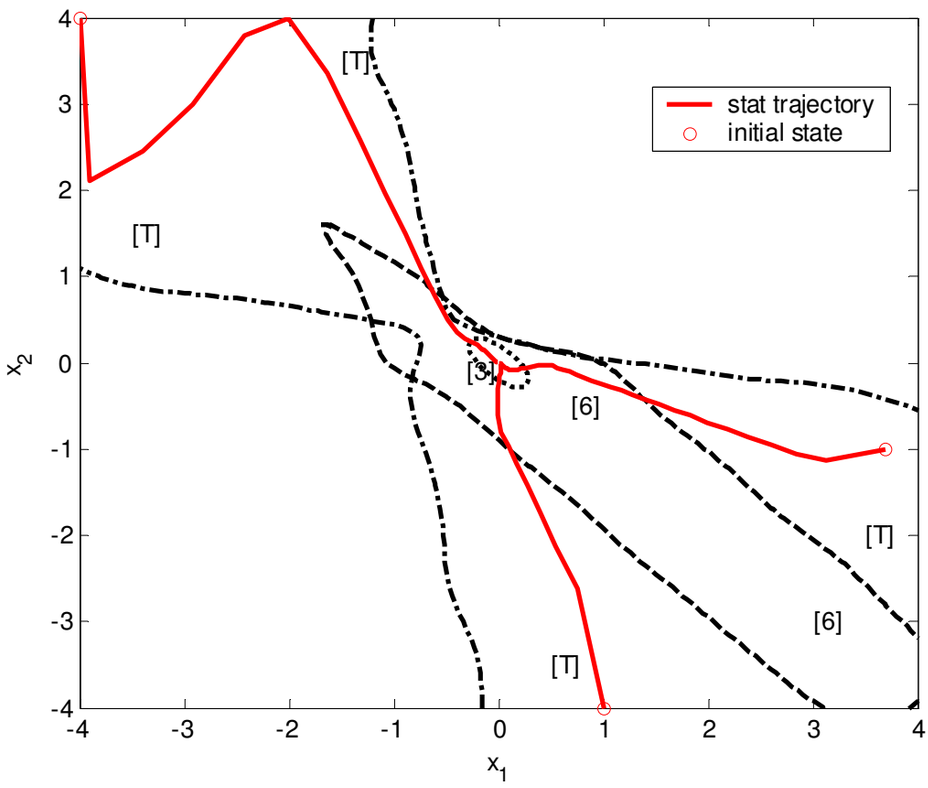


Fig. 2. The closed-loop trajectories of states

In figure 2, the blue ellipsoid is the terminal region in [3] and the region encompassed by black dash lines is the result in [6]. The region encompassed by black solid lines is the terminal region in this paper. We can see, the terminal region in this paper contain the result in [3], but not contain the result in [6] although it is much larger than that in [6]. The reason is that, the terminal region in this paper is the largest one satisfying conditions (C1) and (C2). However, (C1) and (C2) are just the sufficient conditions to guarantee the stability of the controlled system, not the necessary conditions as showed in remark 6. The red solid lines denote the closed-loop trajectories of the selected points. Note that, with the same sampling interval and prediction horizon as those in this paper, these points are not in the regions of attraction of MPC in [3] and [6]. But, they can be leaded to the orgin by using the control law of MPC in this paper.

6. Conclusion

Given the terminal cost, a sequence of subsets of the maximal terminal region are extracted from state space one by one by employing SVM classifier. When one of them is equal to its

succesive one in principle, it is used to serve as the terminal region and it is a good approximation to the maximal terminal region.

7. References

[1] D. Q. Mayne, J. B. Rawlings, C. V. Rao, P. O. M. Scokaert. Constrained model predictive control: stability and optimality. *Automatica*, 2000, 36(6): 789-814.

[2] L. Magni, G. De Nicolao, L. Magnani and R. Scattolini. A stabilizing model based predictive control algorithm for nonlinear systems. *Automatica*, 2001, 37: 1351-1362.

[3] Chen H. and Allgower F.. A quasi-infinite horizon nonlinear model predictive control scheme with guaranteed stability. *Automatica*, 1998, 34: 1205-1217.

[4] M. Cannon, V. Deshmukh and B. Kouvaritakis. Nonlinear model predictive control with polytopic invariant sets. *Automatica*, 2003, 39:1487-1494.

[5] J.A. De Doná, M.M. Seron, D.Q. Mayne, G.C. Goodwin. Enlarged terminal sets guaranteeing stability of receding horizon control. *Systems & Control Letters*, 2002, 47: 57-63.

[6] C.J. Ong，D. Sui and E.G. Gilbert. Enlarging the terminal region of nonlinear model predictive control using the support vector machine method. *Automatica*, 2006, 42: 1011-1016.

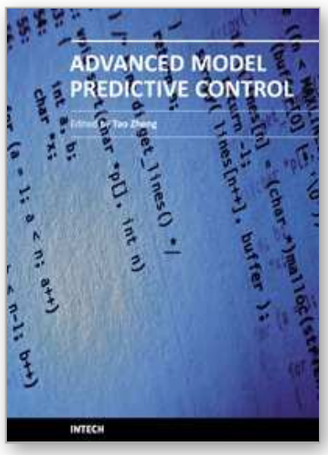
[7] D. Limon, T. Alamo, F. Salas and E. F. Camacho. On the stability of constrained MPC without terminal constraint. *IEEE transactions on automatic control*, 2006, 51(6): 832-836.

[8] D. Limon, T. Alamo, E.F. Camacho. Enlarging the domain of attraction of MPC controllers, *Automatica*, 2005, 41: 629-635.

[9] Alejandro H. González, Darci Odloak, Enlarging the domain of attraction of stable MPC controllers, maintaining the output performance, *Automatica*, 2009, 45: 1080-1085.

[10] Burges C. C.. A tutorial on support vector machines for pattern recognition. *Data Mining and Knowledge Discovery*, 1998, 2(2): 121–167.

[11] Vapnik V. The nature of statistical learning theory. New York, Springer, 1995.



Advanced Model Predictive Control

Edited by Dr. Tao ZHENG

ISBN 978-953-307-298-2
Hard cover, 418 pages
Publisher InTech
Published online 24, June, 2011
Published in print edition June, 2011

Model Predictive Control (MPC) refers to a class of control algorithms in which a dynamic process model is used to predict and optimize process performance. From lower request of modeling accuracy and robustness to complicated process plants, MPC has been widely accepted in many practical fields. As the guide for researchers and engineers all over the world concerned with the latest developments of MPC, the purpose of "Advanced Model Predictive Control" is to show the readers the recent achievements in this area. The first part of this exciting book will help you comprehend the frontiers in theoretical research of MPC, such as Fast MPC, Nonlinear MPC, Distributed MPC, Multi-Dimensional MPC and Fuzzy-Neural MPC. In the second part, several excellent applications of MPC in modern industry are proposed and efficient commercial software for MPC is introduced. Because of its special industrial origin, we believe that MPC will remain energetic in the future.

How to reference
In order to correctly reference this scholarly work, feel free to copy and paste the following:

Yafeng Wang, Fuchun Sun, Youan Zhang, Huaping Liu and Haibo Min (2011). Using Subsets Sequence to Approach the Maximal Terminal Region for MPC, Advanced Model Predictive Control, Dr. Tao ZHENG (Ed.), ISBN: 978-953-307-298-2, InTech, Available from: http://www.intechopen.com/books/advanced-model-predictive-control/using-subsets-sequence-to-approach-the-maximal-terminal-region-for-mpc

INTECH
open science | open minds

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

© 2011 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License, which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen