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Nonlinear model predictive control based on support vector machine and genetic algorithm☆

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ABSTRACT

This paper presents a nonlinear model predictive control (NMPC) approach based on support vector machine (SVM) and genetic algorithm (GA) for multiple-input multiple-output (MIMO) nonlinear systems. Individual SVM is used to approximate each output of the controlled plant. Then the model is used in MPC control scheme to predict the outputs of the controlled plant. The optimal control sequence is calculated using GA with elite preserve strategy. Simulation results of a typical MIMO nonlinear system show that this method has a good ability of set points tracking and disturbance rejection.

1. Introduction

During the past several decades, model predictive control (MPC) technique has become one of the most popular advanced process control (APC) solutions due to its ability to deal with multivariable processes with large time-delays, non-minimum-phase, unstable poles and constraints. The application area has been extended from chemical to aerospace [1–3]. Since 1978, several MPC methods have been proposed [4–6]. However, the idea behind all MPC techniques is the same as that the model of the controlled plant is used to predict the future behavior responds to a candidate control input, which is to be optimized by solving a finite-horizon optimal problem during each sampling period. Then the first element of the optimized input vector is applied to the plant. In this respect, the model of plant is of great importance in MPC methods. Until recently, most industrial applications of MPC have relied on linear models even though the processes are nonlinear [7]. The assumption of process linearity greatly simplifies model development and controller design. However, linear model is inadequate for highly nonlinear processes and processes with large operating regimes [8]. This has led to the development of nonlinear model predictive control (NMPC) [9] where a more accurate nonlinear model is used for process prediction and optimization. First-principle models, based on physical laws, are valid globally and can predict plant dynamics over the whole operating range. However, the development of an accurate first-principle model is difficult and time consuming. Black-box model, which can be obtained through system identification, will be much easier.

There are many nonlinear black-box models such as Volterra models [10], Hammerstein or Wiener type models [11] and artificial neural networks (ANN) [12]. Volterra, Hammerstein and Wiener models can only be applied to special processes. ANN has excellent approximation ability towards nonlinear system. However, it has difficulties in deciding the optimal model structure and it is easy to get trapped in local minimum. Support vector machine (SVM), first proposed by Vapnik [13] in early 1990s, is now considered as an effective way to model nonlinear processes. Compared with ANN, SVM has several advantages such as better generalization capabilities, fewer parameters needed to be adjusted and no local minimum problem [14]. Applying SVM to nonlinear system modeling and controlling has attracted more and more attention [15,16].

Nonlinear model gives more accurate approximation for controlled system, but also makes the optimal control sequence calculation much more difficult. Some researchers try to linearize the nonlinear model at each sampling instant, so MPC proposed for linear systems can be used. However, this may lead to model mismatch which would degrade controller performance. Without linearization, due to the complexity of the optimization problem, classical analytical and numerical optimization techniques usually converge to local minima, thus giving poor solutions even unfeasible solutions. Computational intelligence algorithm, which does not require the objective functions to be derivative or continuous also with the natural advantages to deal with constraints, is of great advantages in this kind of optimization problem. Genetic algorithm (GA), as a represent of evolutional algorithm, has attracted lots of attention owing to its ability to search globally in nonlinear, constrained and non-convex optimization problems.

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This paper proposes a NMPC method based on SVM and GA towards multiple-input multiple-output (MIMO) nonlinear system. SVM is used to approximate the relationship between the inputs and outputs of the nonlinear system. Then the one-step ahead SVM model is used to predict the outputs of the system. For the calculation of optimal control sequences, traditional gradient optimize method is not so convenient because of the SVM models. GA, with the ability to search globally no matter objective function is continuous or derivative is adopted here to calculate optimal control actions at each sampling instant. To maintain the stability of solution, elite preserve strategy is adopted here. The first optimal action is applied to the plant and the whole procedure is repeated at next sampling instant. The rest of the paper is organized as follows: first, a brief review on SVM regression of MIMO nonlinear system is given in Section 2, and then the basic concepts of GA is described in Section 3. The proposed NMPC based on SVM and GA is introduced in Section 4. The simulation results on a typical MIMO nonlinear system in Section 5 show the effectiveness of this method. Finally, conclusion is made in Section 6.

2. Modeling Based on SVM

Consider a discrete-time nonlinear system with R inputs and Q outputs shown in Fig. 1. It is assumed that dynamics of this system can be represented by the Nonlinear Auto-Regressive with eXogenous inputs (NARX) model, as shown in Eq. (1), where $u_r(n)$ is the rth control input of the plant at the time index n, $y_q(n)$ is the qth output of the system, n_i's and m_i's represent the number of past control signals and past outputs involved in the model, respectively.

$$\begin{aligned}&y_q(n)=f_q(u_1(n),\dots,u_1(n-n_1),\dots,u_R(n),\dots,u_R(n-n_R),\\&y_1(n-1),\dots,y_1(n-m_1),\dots,y_Q(n-1),\dots,y_Q(n-m_Q));\\&q=1,2,\dots,Q.\end{aligned} \tag{1}$$

The nonlinear functions f_q are unknown, which means it is needed to model the process through system identification. For this purpose, support vector regression (SVR) is introduced briefly below. The basic idea of SVR is to find a linear function in feature space, where the relationship between inputs and outputs can be represented by the following linear function

$$\hat{y}_q(i)=\langle w_q,\boldsymbol{\Phi}(X_i)\rangle+b_q \tag{2}$$

where $\boldsymbol{\Phi}(X_i)$ is a mapping function from input space to feature space, b_q is the bias term, and $\langle\cdot,\cdot\rangle$ stands for the inner product in the feature space. Using the ε-insensitive loss function [17]

$$|y_q(i)-\hat{y}_q(i)|_\varepsilon=\max\left\{0,|y_q(i)-\hat{y}_q(i)|-\varepsilon\right\} \tag{3}$$

the regression problem turns into a quadratic programming described as follows:

$$\min_{w,b,\xi,\xi^*} J_\varepsilon(w,\xi,\xi^*)=\frac{1}{2}\|w_q\|^2+C\sum_{k=1}^{M}(\xi_i+\xi_i^*) \tag{4}$$

subject to

$$\begin{cases} y_q(i)-\langle w_q,\boldsymbol{\Phi}(X_i)\rangle-b_q\le\varepsilon_q+\xi_i\\ \langle w_q,\boldsymbol{\Phi}(X_i)\rangle+b_q-y_q(i)\le\varepsilon_q+\xi_i^*\\ \xi_i,\xi_i^*\ge 0, i=1,2\dots,N.\end{cases} \tag{5}$$

Here, ε_q is the maximum value of tolerable error of the qth output, ξ_i, ξ_i^* are slack variables, ‖•‖ is the Euclidean norm and $C>0$ is a regularization parameter that describes the trade-off between the model complexity and the tolerance to the error larger than ε_q.

The conditions for optimality yield the following dual quadratic programming (QP) problem:

$$\min\left[\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}K(X_i,X_j)\left(a_{qi}-a_{qi}^*\right)\left(a_{qj}-a_{qj}^*\right)+\varepsilon_q\sum_{i=1}^{N}\left(a_{qi}+a_{qi}^*\right)-\sum_{i=1}^{N}y_q(i)\left(a_{qi}-a_{qi}^*\right)\right] \tag{6}$$

subject to the constraints

$$\begin{aligned}&0\le a_{qi},a_{qi}^*\le C\\&\sum_{i=1}^{N}\left(a_{qi}-a_{qi}^*\right)=0, i=1,2\dots,N\end{aligned} \tag{7}$$

where a_{qi}, a_{qi}^*, a_{qj}, a_{qj}^* are the Lagrange multipliers, $K(X_i,X_j)=\boldsymbol{\Phi}(X_i)^{\mathrm{T}}\cdot\boldsymbol{\Phi}(X_j)$ is the kernel function which meets the Mercer condition that handles the inner product in the feature space and hence the exact form of $\boldsymbol{\Phi}(X_k)$ does not need to be known [18]. Solve the QP problem ((7) and (8)) to obtain the optimal values of a_{qi}, a_{qi}^* and then get b_q through Karush–Kuhn–Tucker (KKT) [19,20] condition. When only the support vectors corresponding to the non-zero $(a_{qi}-a_{qi}^*)$ are considered, the nonlinear regression function becomes

$$\hat{y}_q(i)=\sum_{i=1(i\in SV)}^{\#SV}\left(a_{qi}-a_{qi}^*\right)K(X_i,X_j)+b_q \tag{8}$$

where # SV denotes the number of support vectors. The SVM model is sparse for all the training data represented by only support vectors. For detailed information please refer to [18].

For the MIMO system in Fig. 1 described by Eq. (1), the individual SVM is used for each output of the plant. Suppose the training data set for the qth output of the system is in the form below:

$$\begin{aligned}T_q=&\{u_1(k),\dots,u_1(k-n_1),\dots,u_R(k),\dots,u_R(k-n_R),\\&y_1(k-1),\dots,y_1(k-m_1),\dots,y_Q(k-1),\dots,y_Q(k-m_Q);y_q(k)\}_{k=1}^{k=N}\\=&\left\{X_k;y_q(k)\right\}_{k=1}^{k=N}\end{aligned} \tag{9}$$

where X_k is the kth input data point in the input space, $y_q(k)\in R$ is the corresponding output value and N is the number of data point. Then, the training set T_q can be used to train the qth SVM model of the plant. With only the support vectors considered, the model becomes just like Eq. (8).

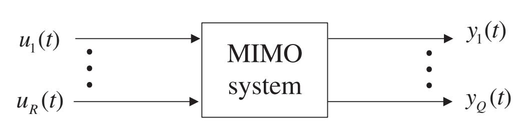

Fig. 1. MIMO system.

3. Genetic Algorithm

GA is a global optimization search method based on the rule of "survival of the fittest" inspired by Darwinian's biological evolutionary theory. It is potential parallel and robust, and has excellent global searching ability. The three main operators in GA are selection, crossover and mutation. These operators are explained below.

To start the optimization, GA randomly produces a population including N initial solutions which are consisted of encoded strings. Then GA uses the three genetic operators to yield N new solutions. In the selection operation, each solution of the current population is evaluated by its fitness, which is normally represented by the value of some objective function. Individuals with higher fitness are more likely to be