ISSN NO. 2320-5407

Journal homepage: http://www.journalijar.com

INTERNATIONAL JOURNAL OF ADVANCED RESEARCH

RESEARCH ARTICLE

A New Sliding-mode Model Predictive Controller for Output Tracking of Nonlinear Systems with Online Optimization

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Manuscript Info

Manuscript History:

Received: 15 July 2015
Final Accepted: 22 August 2015
Published Online: September 2015

Key words:
Model-predictive control; on-line optimization; nonlinear control; tracking; sliding-mode control

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Abstract

A model predictive control method for nonlinear systems is presented resulting from a new sliding manifold definition. The sliding-mode control with new manifold drives dynamics of a given nonlinear system to a stable sliding surface faster compared to standard counterparts. The new manifold definition is further exploited for a straightforward derivation of discrete-time predictive controller with on-line optimization in dynamics of both deterministic and stochastic components. Simulation results for a second-order nonlinear system show that new predictive controller leads to more successful tracking of a given target trajectory compared to conventional sliding-mode controller for the system studied with suitably determined real-time operational conditions such as time and control update terms.

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Introduction

Model predictive control (MPC), which is also known as receding horizon control, aims at determining an optimal open-loop control sequence as a means of trajectory planning given system constraints, [1]. Despite theoretical attractiveness of MPC, especially for linear systems, almost all systems are nonlinear. Nonlinear MPC (NMPC) has a major disadvantage that the associated computational time interval and boundary constraints may impose hard-to-solve complicated optimality conditions about stability against un-modeled components even for simple nonlinear systems, [2]. A solution is to employ a closed-loop control with non-terminal conditions to correct discrepancies in state dynamics which may arise due to uncertainties involved where an open-loop cost function to be minimized is accompanied with a candidate Lyapunov function, [3]-[4]. Sliding-mode control (SMC), [5]-[6], is a closed-loop control method which gives rise to system dynamics robust against uncertainties and external disturbances. It mainly consists of reaching and sliding-mode phases, respectively. In the former, the system trajectory that has been set off a bounded initial condition is forced to converge to a predefined sliding surface in a finite time while the latter refers to dynamics on the sliding surface presumably reached. In SMC, total control is a superposition of nominal and additive discontinuous terms where the nominal control drives plant dynamics to the sliding surface under nominal conditions while the additive control aims at maintaining system behavior on that surface. Thus, it is advantageous to integrate MPC and SMC, which is abbreviated as SM-MPC.

In SM-MPC, off-line control sequence, which has been obtained in predictive stage, is further updated in closed-loop with SMC. For example, in [7] and [8], SMC is employed as a discrete-time compensator where the next control sequence is estimated resulting from an optimization. In [9], the ensemble of control terms obtained from MPC is regarded as a reference control generator that is further regulated by the control obtained from an integral sliding mode (ISM) controller. The major problem with major SM-MPC methods is that the control for standard SMC lags the residual error given a particular state through the control horizon, which causes excessive chattering in closed-loop and which is then to be disseminated at updates in MPC. If the control is updated on-line to correct predicted dynamics of system along the sliding manifold, overall operation will exhibit longer delay in tracking compared to SMC-only operation.

In this study, a model predictive control scheme for nonlinear systems is described. New controller is obtained from a new sliding manifold definition. The sliding-mode control with new manifold brings dynamics of a given nonlinear system to a stable sliding surface faster than the standard counterparts. The new manifold definition is further exploited for a straightforward derivation of discrete-time predictive controller with on-line optimization in dynamics of both deterministic and stochastic components. Simulation results for a second-order nonlinear system demonstrate that the new predictive controller leads to more successful tracking a given target trajectory compared to conventional sliding-mode controller for the system studied with suitably determined real-time operational conditions such as time and control update terms.

Overview of Sliding-mode Control and Description of New Manifold

We consider an input-affine nonlinear multi-input multi-output (MIMO) system

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u} + \boldsymbol{\upsilon} \\ \mathbf{y} &= \mathbf{h}(\mathbf{x}) \end{aligned} \tag{1}$$

where $\mathbf{x}$, $\mathbf{u}$, $\mathbf{y}$ and $\boldsymbol{\upsilon}$represent state, control/input, measured/estimated output and external disturbance vectors, respectively, while **f**, **g** and **h** are respective smooth vector fields of suitable dimensions. The input coupling matrix **g** is assumed to be invertible. Given a target trajectory, $\mathbf{y}_d(t)$, the output tracking error is $\mathbf{e}(t) = \mathbf{y}(t) - \mathbf{y}_d(t)$. For the i-th coordinate tracking error $e_i(t) = y_i(t) - y_{d,i}(t)$, and a constant $\lambda_i > 0$, the standard sliding manifold is defined as

$$s_i(t) = \left(\frac{d}{dt} + \lambda_i\right)^{(r_i - 1)} \Psi[e_i(t)] \tag{2}$$

where $r_i \geq 1$ is the relative degree. In (2), $\Psi[e_i(t)] = e_i(t)$ and $\Psi[e_i(t)] = \int_0^t e_i(\tau)d\tau$ correspond to conventional and integral-type SMC (ISMC), respectively. For manifold in (2), the nominal control $\hat{u}_i$is derived by solving the equation $\dot{s}_i(t) = 0$ with nominal model. The overall control law is then given by $u_i = \hat{u}_i + \delta u_i$ where the additional control δu_i is employed for correcting the adverse effects due to bounded disturbance υ_i and other unknown uncertainties. It is usually given by $\delta u_i = -\kappa_i \varphi(s_i)$ where $\varphi(.)$ is a discontinuous function such as saturation 'sat'. The parameter κ_i is an adaptive gain to ensure that the sliding manifold dynamics satisfies the convergence condition $\dot{s}_i(t)s_i(t) \leq -\eta_i|s_i(t)|$ with a constant $\eta_i > 0$ for presumed bounds on disturbance and uncertainties. Under this condition, the standard SMC laws have a reach time, which is time for trajectory of the output to reach the surface $s_i(t) = 0$ starting at any bounded $s_i(0)$, upper-bounded by $|s_i(0)|/\eta_i$. It is seen that the nominal control for conventional SMC does not involve error term itself explicitly. Hence, the resulting control will lag the error, which causes chattering. On the other hand, the nominal control for ISMC includes error, which yields faster operation at a cost of possible instability and sensitivity in tracking fast variations in target trajectory.

A suitable solution to the shortcomings cited above is to devise a nominal control, which can be obtained by combining both SMCs. We consider a manifold $\dot{s}_i(t) + \lambda_i s_i(t) = \mathrm{e}^{-\lambda_i t}\frac{d s_i \mathrm{e}^{\lambda_i t}}{dt}$ where $s_i(t)$ refers to conventional sliding manifold. With this new manifold, the nominal control is obtained based on the condition $\dot{s}_i(t) + \lambda_i s_i(t) = 0$, [6]. The convergence rule for new manifold is given by $\dot{s}_i(t)s_i(t) \leq -\eta_i|s_i(t)| - \lambda_i s_i^2(t)$ referring to a system trajectory which reaches surface $s_i(t) = 0$ with time $t_{reach,i} \leq \frac{1}{\lambda_i}\ln\left[1 + \frac{\eta_i}{\lambda_i}|s_i(0)|\right] < \frac{|s_i(0)|}{\eta_i}$. Thus, for any bounded $s_i(0)$, reach time for new method is smaller than that of standard SMCs. New SMC scheme has been applied for output tracking and navigation of under-actuated surface vessels study under noisy measurements and modeling uncertainties with an extended Kalman filter (EKF) as an observer in [10].

Proposed Model-predictive Controller Based on New Sliding-mode Algorithm

For devising a predictive controller, we combine new manifold definition and respective convergence law in discrete-time, which yields

$$s_{i,k+1}^2 \leq \left[s_{i,k}^2 - 2\eta_i|s_i(t)|\right]\mathrm{e}^{-2\lambda_i\Delta t_k} < s_{i,k}^2(t) \tag{3}$$

for the k-th sampling time t_k and update interval Δt_k. Then, for a horizon depth N>0 and initial time instance $q \geq 0$, $s_{i,q}^2 - s_{i,q+N}^2 = \sum_{k=q}^{q+N-1} s_{i,k}^2 - s_{i,k+1}^2 \geq \sum_{k=q}^{q+N-1} s_{i,k}^2\left(1 - \mathrm{e}^{-2\lambda_i\Delta t_k}\right) + 2\eta_i\Delta t_k|s_i(t)|\mathrm{e}^{-2\lambda_i\Delta t_k} > 0$, which implies that $\sum_{k=q}^{q+N} s_{i,k}^2 \leq M < \infty$. With use of Lie derivatives for (1) and by rearranging resulting terms into the new manifold, sliding-mode dynamics can be decomposed into deterministic ($\mathbf{s}$) and stochastic uncertain/random noise ($\boldsymbol{\varepsilon}$) terms as

$$\begin{aligned} \mathbf{s}_{k+1} &= \boldsymbol{\Lambda}_k\mathbf{s}_k + \boldsymbol{\Psi}_k\delta\mathbf{u}_k = \mathrm{g}_s(\mathbf{s}_k, \delta\mathbf{u}_k) \\ \boldsymbol{\varepsilon}_{k+1} &= \boldsymbol{\Omega}_k\boldsymbol{\varepsilon}_k + \boldsymbol{\Xi}_k\hat{\mathbf{u}}_k = \mathrm{g}_\varepsilon(\boldsymbol{\varepsilon}_k, \hat{\mathbf{u}}_k) \end{aligned} \tag{4}$$

respectively, where column vectors $\mathbf{s}_k = \left[s_{i,k}\right]_{i=1}^m$, $\delta\mathbf{u}_k = \left[\delta u_{i,k}\right]_{i=1}^m$, $\hat{\mathbf{u}}_k = \left[\hat{u}_{i,k}\right]_{i=1}^m$, $\boldsymbol{\varepsilon}_k = \left[\varepsilon_{i,k}\right]_{i=1}^m$ and diagonal matrices $\boldsymbol{\Lambda}_k = \mathrm{diag}\left\{\mathrm{e}^{-\lambda_i\Delta t_k}\right\}_{i=1}^m$, $\boldsymbol{\Psi}_k = \Delta t_k\mathrm{diag}\left\{\beta_{i,k}\mathrm{e}^{-\lambda_i\Delta t_k}\right\}_{i=1}^m$, $\boldsymbol{\Omega}_k = \Delta t_k\boldsymbol{\Lambda}_k$, $\boldsymbol{\Xi}_k = \Delta t_k\mathrm{diag}\left\{\vartheta_{\beta_{i,k}}\mathrm{e}^{-\lambda_i\Delta t_k}\right\}_{i=1}^m$. Here, notation $\left[a_{i,k}\right]_{i=1}^m$ denotes column vector $\left[a_{1,k} \dots a_{m,k}\right]^T$. For the i-th coordinate, term $\varepsilon_{i,k} = \vartheta_{\alpha_{i,k}} + \upsilon_{i,k}$ accounts for uncertainty $\vartheta_{\alpha_{i,k}}$ in $\alpha_{i,k} = L_f^{(r_i)}h_i(\mathbf{x}_k)$ and disturbance $\upsilon_{i,k}$ while $\vartheta_{\beta_{i,k}}$ in $\boldsymbol{\Xi}_k$ refers to uncertainty in $\beta_{i,k} = L_{g_i}L_f^{(r_i-1)}h_i(\mathbf{x}_k)$, respectively. We consider variation of $\sum_{k=q}^{q+N} s_{i,k}^2$ for updating the pre-computed off-line control sequence as a means of on-line optimization. Given a desired trajectory, a sliding-mode model predictive algorithm can be developed by minimizing the cost function

$$J = \varphi\left(\mathbf{s}_{q+N}\right) + \sum_{k=q}^{q+N-1}\Gamma(\mathbf{s}_k, \delta\mathbf{u}_k) \tag{5}$$

where $\Gamma(\mathbf{s}_k, \delta\mathbf{u}_k) = \left(\frac{1}{2}\right)\mathbf{s}_k^T\mathbf{s}_k + \left(\frac{1}{2}\right)\delta\mathbf{u}_k^T\mathbf{P}\delta\mathbf{u}_k$ with terminal term $\varphi\left(\mathbf{s}_{q+N}\right) = \left(\frac{1}{2}\right)\mathbf{s}_{q+N}^T\mathbf{s}_{q+N}$. In (5), $\mathbf{P}$ is a suitable positive semi-definite matrix to ensure a bounded J through $\delta\mathbf{u}_k$. The Lagrangian for optimizing J in (5) is given by

$$J = \varphi\left(\mathbf{s}_{q+N}\right) - \boldsymbol{\rho}_{q+N}^T\mathbf{s}_{q+N} + \sum_{k=q+1}^{q+N-1}\left[H_k - \boldsymbol{\rho}_k^T\mathbf{s}_k\right] + H_q \tag{6}$$

where the respective Hamiltonian is $H_k = \Gamma(\mathbf{s}_k, \delta\mathbf{u}_k) + \boldsymbol{\rho}_{k+1}^T\mathrm{g}_s(\mathbf{s}_k, \delta\mathbf{u}_k)$ with co-state vector $\boldsymbol{\rho}_k = \left[\rho_{i,k}\right]_{i=1}^m$. Co-state vectors concerning variation of J according to (6) are obtained as

$$\begin{aligned} \boldsymbol{\rho}_{q+N}^T &= \frac{\partial\varphi}{\partial\mathbf{s}_{q+N}} = \mathbf{s}_{q+N}^T \\ \boldsymbol{\rho}_k^T &= \frac{\partial H_k}{\partial\mathbf{s}_k} = \mathbf{s}_k^T + \boldsymbol{\rho}_{k+1}^T\frac{\partial\mathrm{g}_s}{\partial\mathbf{s}_k} = \mathbf{s}_k^T + \boldsymbol{\rho}_{k+1}^T\boldsymbol{\Lambda}_k \end{aligned} \tag{7}$$

where $k = q+1, \dots, q+N$. Then, input-constraint variation of J to be minimized on-line is then found to be

$$\Delta J \approx \left[\sum_{k=q}^{q+N-1}\left(\frac{\partial H_k}{\partial\delta\mathbf{u}_k}\right)^T\Delta(\delta\mathbf{u}_k)\right] + \boldsymbol{\rho}_q^T\Delta\mathbf{s}_q \tag{8}$$

where 'Δ' stands for differential variation. Substituting $\boldsymbol{\rho}_{k+1}^T$ in (7) into $\left(\frac{\partial H_k}{\partial\delta\mathbf{u}_k}\right)^T = \delta\mathbf{u}_k^T\mathbf{P} + \boldsymbol{\rho}_{k+1}^T\boldsymbol{\Psi}_k$ with $\delta u_{i,k} = -\kappa_i\emptyset_i\mathrm{sat}\left(\frac{\rho_{i,k}-s_{i,k}}{\emptyset_i}\right)$ for $\kappa_i, \emptyset_i > 0$ and choosing $\mathbf{P} = \Delta t_k\mathrm{diag}\left\{\hat{\beta}_{i,k}\right\}_{i=1}^m$ yield

$$\Delta J \approx \boldsymbol{\rho}_q^T\Delta\mathbf{s}_q - \sum_{k=q}^{q+N-1}\Delta t_k\,\boldsymbol{\vartheta}_{\beta_k}^T\left[\Delta\left(\delta u_{i,k}\right)\delta u_{i,k}\right]_{i=1}^m \tag{9}$$

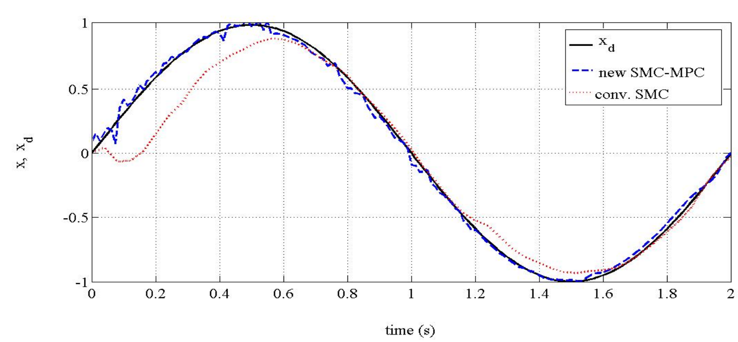
where $\boldsymbol{\vartheta}_{\beta_k} = [\vartheta_{\beta_{i,k}}]_{i=1}^{m}$ is vector of uncertainties in $\beta_{i,k}$. By assuming that uncertainties in coordinates are statistically uncorrelated and stationary, then the mean and variance of ΔJ are given by $\mu_{\Delta J} \propto \boldsymbol{\rho}_q^T \Delta \mathbf{s}_q - \boldsymbol{\mu}_{\vartheta_\beta}^T \sum_{k=q}^{q+N-1} \Delta t_k [\Delta(\delta u_{i,k}) \delta u_{i,k}]_{i=1}^{m}$ with $\boldsymbol{\mu}_{\vartheta_\beta} = [\mu_{\vartheta_{\beta_i}}]_{i=1}^{m}$ and $\sigma_{\Delta J}^2 \propto (\boldsymbol{\sigma}_{\vartheta_\beta}^2)^T \sum_{k=q}^{q+N-1} (\Delta t_k)^2 [[\Delta(\delta u_{i,k}) \delta u_{i,k}]^2]_{i=1}^{m}$ with $\boldsymbol{\sigma}_{\vartheta_\beta}^2 = [\sigma_{\vartheta_{\beta_i}}^2]_{i=1}^{m}$, respectively. It should be noted that the initial and subsequent variations in sliding-mode vector are pre-computed. The additive control to be applied in the next control update can be predicted based on gradient descent as $\delta \mathbf{u}_{k+1} \approx \delta \mathbf{u}_k + \Delta(\delta \mathbf{u}_k)(\partial H_k / \partial \delta \mathbf{u}_k)$ where $\Delta(\delta \mathbf{u}_k)$ is to be adjusted to ensure decrease in $|\Delta J|$.

Stochastic noisy or uncertain input to system model $\boldsymbol{\varepsilon}_{k+1} = \boldsymbol{\Omega}_k \boldsymbol{\varepsilon}_k + \Xi_k \hat{\mathbf{u}}_k = g_\varepsilon(\boldsymbol{\varepsilon}_k, \hat{\mathbf{u}}_k)$ in (4) represents a vector of uncertainty state variables $\varepsilon_{i,k} = \vartheta_{\alpha_{i,k}} + v_{i,k}$. Assuming that uncertainties $\vartheta_{\alpha_{i,k}}$ and $\vartheta_{\beta_{i,k}}$ are stationary and uncorrelated, respective statistical mean/expectation and variance in $\varepsilon_{i,k}$ are $\mu_{\varepsilon_{i,k+1}} \propto \mu_{\varepsilon_{i,k}} + \vartheta_{\beta_i} \hat{u}_{i,k}$ and $\sigma_{\varepsilon_{i,k+1}}^2 \propto |\hat{u}_{i,k}|^2 \sigma_{\vartheta_{\beta_i}}^2 + \sigma_{\varepsilon_{i,k}}^2$, respectively. It is seen that the mean and variance of noisy terms are determined by nominal control. Since nominal control is computed under known conditions, noisy plant dynamics can be predicted *a priori* and hence controlled along with pre-specified nominal behaviour.

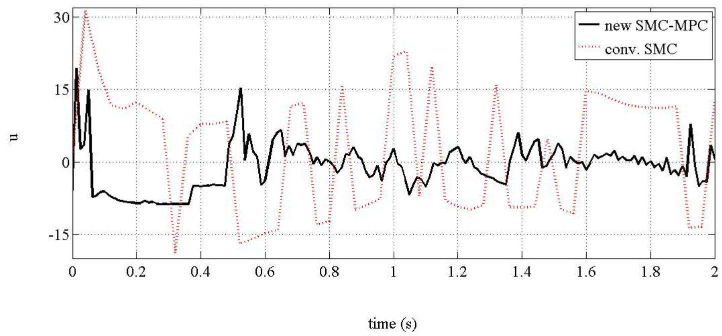
Application of New Predictive Controller

New predictive controller was designed for tracking of a second-order system given by $\ddot{x} = -a(t)\dot{x}^2 \cos 3x + u$, [5], where uniform random model uncertainty and external disturbance are all modeled by $a(t) = 1 + |\sin t|$. For a desired trajectory $x_d(t)$ and tracking error $e = x - x_d$, the new sliding manifold is given by $\dot{s}(t) + \lambda s(t)$ where $s(t) = \dot{e} + \lambda e$, which yields nominal control $\hat{u} = \ddot{x}_d + 1.5\dot{x}^2 \cos 3x - 2\lambda \dot{e} - \lambda^2 e$. Given initial conditions x_0 and s_0, discretised sequence of $\hat{u}$ for k = 0, …, N-1 was obtained by sampling it at 0.01s and then used to predict the sequence of x_k and s_k for k = 1, …, N, off-line with (1) and (4), respectively. Then, co-states ρ_k were computed for k = N, …, 1 which was then utilized in discrete sequence of the additional control term $\delta u = (0.5\dot{x}^2 |\cos 3x| + \eta) \operatorname{sat}\left(\frac{\rho - s}{\phi}\right)$. In simulations with trajectory tracking problem, the SMC parameters were set as $\lambda = 4$, $\eta = 10$, and $\phi = 0.01$. The prediction parameters N and Δt_k were estimated for $|\Delta J| \leq 0.005$ with $s_0 = \Delta s_0 = 0.01$. For the sampling rate used, $|\Delta J|$ was found to decrease faster if $0.12\text{s} < \sum_{k=1}^{N} \Delta t_k < 0.19\text{s}$, e.g. for N=20 and $0.006\text{s} < \Delta t_k < 0.0095\text{s}$.

For comparison purpose, the conventional sliding-mode controller was also designed with the first-order manifold $s(t) = (\dot{x} - \dot{x}_d) + \lambda_{SMC}(x - x_d)$ and reaching law $\dot{s}(t)s(t) < -\eta_{SMC}|s(t)|$ where λ_{SMC} and η_{SMC} are both positive constants. The nominal control for this manifold was obtained by solving $\dot{s}(t) = 0$ while the additional control was formed with the hyperbolic tangent function as 'tanh(s/ϕ)' where ϕ>0. Total control for conventional SMC is found as $u = \ddot{x}_d - \lambda_{SMC}\dot{x} + 1.5\dot{x}^2 \cos 3x - (0.5\dot{x}^2 |\cos 3x| + \eta_{SMC}) \tanh(s(t)/\varphi_{SMC})$. For this controller, the parameters were chosen such that possible minimum tracking delay is attained: $\lambda_{SMC} = 4$, $\eta_{SMC} = 10$ and $\phi_{SMC} = 0.01$. Fig. 1 shows the tracking performances and control efforts exerted by the new controller and conventional SMC for desired trajectory $x_d(t) = \sin \pi t$ with initial conditions $x(0) = \dot{x}(0) = 0$.



(a)



(b)

Fig. 1 (a) Tracking performance and (b) control input with new SM-MPC and conventional SMC controllers.

Above results indicate that the new SM-MPC controller is able track the chosen target trajectory with smaller error and control inputs compared to conventional SMC for whole simulation time interval. Furthermore, as time elapses, new SM-MPC exhibits almost stationary behavior in both terms with smaller variation.

Conclusions

A model predictive controller for nonlinear systems is introduced based on a new sliding manifold. The sliding-mode control corresponding to new manifold drives dynamics of a given nonlinear system to a stable sliding surface faster than the standard counterparts. The new manifold definition is shown to yield straightforward derivation of discrete-time predictive controller with on-line optimization for dynamics of both deterministic and stochastic components in linear terms. Simulation results for a second-order nonlinear system reveal that the new predictive controller is more successful in tracking of a desired trajectory compared to conventional sliding-mode controller for the system studied with suitably determined real-time operational conditions such as time and control update terms.

Acknowledgement

This work was partially supported by the Office of Naval Research under ONR Grant number N00014-09-1-1195.

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