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Sequential ℓ_1 Quadratic Programming for Nonlinear Model Predictive Control

Dimitri Boiroux, John Bagterp Jørgensen

*Department of Applied Mathematics and Computer Science,
Technical University of Denmark, DK-2800 Kgs. Lyngby, Denmark.*

Abstract: In this paper, we present and describe a computationally efficient sequential ℓ_1 quadratic programming ($S\ell_1$ QP) algorithm for Nonlinear Model Predictive Control (NMPC). We use a tailored trust region sequential quadratic programming for the solution of the optimal control problem (OCP) involved in the NMPC algorithm. We use a multiple shooting approach for numerical integration and sensitivity computation. A second order correction ensures a faster convergence of the SQP algorithm. We exploit the structure of the OCP by using an efficient primal-dual interior point algorithm based on Riccati factorizations and a block diagonal BFGS update of the Hessian matrix. The complexity scales linearly with the prediction horizon length. We numerically evaluate and compare the performance of our algorithm on a numerical example.

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Keywords: Nonlinear model predictive control, trust region algorithm, sequential quadratic programming

1. INTRODUCTION

Nonlinear model predictive control (NMPC) refers to model-based control algorithms where the model consists of nonlinear differential equations (Allgöwer et al. (1999)). The review from Qin and Badgwell (2000) mentions at least 88 industrial applications of NMPC. Some examples of research topics using NMPC include finance (Chong et al. (2015)), oil recovery (Capolei et al. (2012)), industrial processes (Wang et al. (2016)), automotive applications (Liu et al. (2015)), or biomedical engineering (Boiroux et al. (2010); Zavitsanou et al. (2016)). At each time sample, NMPC-based algorithms require the solution of a nonlinear optimal control problem (OCP). For some applications, e.g. in biomedical engineering, it is important that the control algorithm can be implemented on a portable system. Therefore, the algorithms must be designed in a computationally efficient and robust way that can be implemented on an embedded system.

Sequential quadratic programming (SQP) refers to a set of iterative methods for the numerical solution of NLPs. At each iteration, the NLP is approximated by a quadratic program (QP). The equality and inequality constraints are linearized at each iteration. The objective function of the QP sub-problem is a quadratic approximation of the Lagrangian. SQP algorithms can be subdivided between local SQP methods and trust region algorithms.

In local SQP methods, the optimization algorithm computes a search direction at each iteration using a Newton or quasi-Newton method. A line search computes a scaling factor to ensure global convergence. Under some assumptions, local SQP algorithms converge globally with a superlinear rate of convergence (Nocedal and Wright (2006)).

In trust-region methods, the length of the search direction step is bounded to be within a certain region. The size of the trust region is updated at each SQP iteration to ensure a fast convergence. One of the challenges of trust region methods is to ensure feasibility of the QP sub-problem. To circumvent the possible infeasibility of the sub-problem, a popular solution is to use soft constraint formulations of the equality and/or inequality constraints. Plantenga (1994) provides a review of approaches to handle inconsistent constraints in trust region algorithms, and Tenny et al. (2004) describe a trust region SQP algorithm for NMPC. Software for the numerical solutions of NLPs have been developed, e.g. SNOPT (Gill et al. (2005)). These software are suited for general SQPs, but do not exploit the sparse and specific structure of OCPs.

This paper presents a tailored trust region algorithm based on sequential ℓ_1 quadratic programming ($S\ell_1$ QP) to solve OCPs. $S\ell_1$ QP algorithms have been introduced by Fletcher (1987). They ensure feasibility of the QP sub-problem by adding ℓ_1 penalties on equality and inequality constraint violations. In practice, we implement the ℓ_1 penalties by using slack variables. When solving the OCP, one computational bottleneck is the computation of the search direction arising in the QP sub-problem. Works from Wang and Boyd (2010) and Domahidi et al. (2012) show computationally efficient methods for computing the search direction. In this paper, we utilize Riccati recursions (Rao et al. (1998); Jørgensen et al. (2012); Frison and Jørgensen (2013); Hagdrup et al. (2017)).

Section 2 describes the OCP formulation. Section 3 presents the different steps of the trust region algorithm. Section 4 illustrates and discusses the algorithm on the Van der Pol oscillator. Section 5 summarizes the contributions of this paper.

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2. PROBLEM FORMULATION

We assume a zero-order hold parametrization of the input vector, $u(t)$. At each iteration, the NMPC algorithm solves an optimal control problem (OCP) in the Bolza form

$$\min_{\{x_{k+1}, u_k\}_{k=0}^{N-1}} \phi = \sum_{k=0}^{N-1} G_k(x_k, u_k) + h(x_N), \quad (1a)$$

$$\text{s.t.} \quad x_0 = \hat{x}_{0|0}, \quad (1b)$$

$$b_k := F_k(x_k, u_k, d_k) - x_{k+1} = 0, \quad (1c)$$

$$u_{\min} \leq u_k \leq u_{\max}. \quad (1d)$$

Remark 1. In this formulation, we assume that x_0 is fixed and is not an optimization variable.

The function describing the state dynamics is

$$F_k = \{x(t_{k+1}) : \dot{x}(t) = f(x(t), u_k, d_k), x(t_k) = x_k\}. \quad (2)$$

The objective function (1a) consists of discrete stage costs, G_k , and a terminal cost, $h(x_N)$. The discrete time stage cost is

$$G_k = \int_{t_k}^{t_{k+1}} g(x(t), u_k) dt. \quad (3)$$

To have a compact notation, we rewrite the decision variables, \tilde{x} , as

$$\tilde{x} = [u'_0 \ x'_1 \ u'_1 \ x'_2 \ \dots \ x'_{N-1} \ u'_{N-1} \ x'_N]', \quad (4)$$

and we compute the residuals as

$$b(\tilde{x}) = \begin{bmatrix} F_0(x_0, u_0, d_0) - x_1 \\ F_1(x_1, u_1, d_1) - x_2 \\ \vdots \\ F_{N-1}(x_{N-1}, u_{N-1}, d_{N-1}) - x_N \end{bmatrix}. \quad (5)$$

The objective function, $\phi(\tilde{x})$, is

$$\phi(\tilde{x}) = \sum_{k=0}^{N-1} G_k(x_k, u_k, d) + H(x_N). \quad (6)$$

Using these notations, we reformulate the discrete-time OCP (1) as a constrained optimization problem in the form

$$\min_{\tilde{x}} \phi(\tilde{x}), \quad (7a)$$

$$\text{s.t.} \quad b(\tilde{x}) = 0, \quad (7b)$$

$$c(\tilde{x}) \geq 0, \quad (7c)$$

The first order KKT conditions of the constrained nonlinear optimization problem (7) are

$$\nabla_{\tilde{x}} \mathcal{L}(\tilde{x}, y, z) = \nabla_{\tilde{x}} \phi(\tilde{x}) - \nabla_{\tilde{x}} b(\tilde{x}) y - \nabla_{\tilde{x}} c(\tilde{x}) z = 0, \quad (8a)$$

$$b(\tilde{x}) = 0, \quad (8b)$$

$$c(\tilde{x}) \geq 0, \quad (8c)$$

$$z \geq 0, \quad (8d)$$

$$c_i(\tilde{x}) z_i = 0 \quad \forall i \in \mathcal{I}, \quad (8e)$$

where y and z are the Lagrange multipliers associated to the equality (7b) and the inequality constraints (7c), respectively. We use these conditions to check the convergence of the algorithm.

3. TRUST REGION ALGORITHM

In trust region algorithms, we ensure that the step, p , lies in a region where the QP approximation of the

initial problem (7) is sufficiently accurate, i.e. we add the following constraint

$$\|p\| \leq \Delta, \quad (9)$$

where Δ is updated at each SQP iteration. Usually, it is not possible to ensure that the QP sub-problem with the additional constraint (9) is feasible. To solve the nonlinear program (7), we use a sequential ℓ_1 quadratic program ($S\ell_1$ QP) algorithm. We use a multiple-shooting algorithm for the numerical integration of the objective function and the sensitivity computation (Bock and Plitt (1984); Diehl et al. (2009); Boiroux et al. (2010)). Usually, the $S\ell_1$ QP sub-problem is

$$\min_{p, v, w, t} \frac{1}{2} p' H p + g' p + \mu \sum_{i \in \mathcal{E}} (v_i + w_i) + \mu \sum_{i \in \mathcal{I}} t_i, \quad (10a)$$

$$\text{s.t.} \quad \nabla b(\tilde{x}_k)' p + w - v = -b, \quad (10b)$$

$$\nabla c(\tilde{x}_k)' p \geq -c(\tilde{x}_k) - t, \quad (10c)$$

$$v, w, t \geq 0, \quad (10d)$$

$$\|p\| \leq \Delta. \quad (10e)$$

in which \mathcal{E} is the set of equality constraints and \mathcal{I} is the set of inequality constraints. For simplicity, we use the infinity norm for the constraint (10e), such that it becomes a bound constraint

$$-\Delta \leq p_i \leq \Delta. \quad (11)$$

The addition of the slack variables, v , w and t , penalizes the violation of equality and/or inequality constraints and ensures that the QP (10) is always feasible. The parameter $\mu > 0$ is updated at each iteration. The update of μ ensures that sufficiently large steps p are taken while being able to converge to a feasible solution of the NLP (7). The following subsections describe the different steps of the trust region algorithm.

Remark 2. The slack variables associated to equality constraints, v_i and w_i , are usually required to ensure the feasibility of the $S\ell_1$ QP subproblem (10) in the case where the trust region is too small. However, in the case where the inequality constraints are bound constraints, the inequality constraints (1d) are always feasible. Therefore, we can reduce the problem size by omitting the slack variables t_i .

3.1 Sensitivity computation

The main computational challenges in the SQP algorithm are the computation of the objective function, $\phi(\tilde{x})$, the derivatives of the objective function, $\nabla_{\tilde{x}} \phi(\tilde{x})$, the dynamics, $b(\tilde{x})$, and the sensitivities, $\nabla_{\tilde{x}} b(\tilde{x})$. $b(\tilde{x})$ and $\phi(\tilde{x})$ are computed by evaluation of (2) and (3), respectively.

For instance, the gradients of the equality constraints, $b(\tilde{x})$, with respect to the decision variable, \tilde{x} , can be written for a prediction horizon $N = 2$ as

$$\nabla_{\tilde{x}} b = \begin{bmatrix} B_0 & 0 & 0 \\ -I & A_1 & 0 \\ 0 & B_1 & 0 \\ 0 & -I & A_2 \\ 0 & 0 & B_2 \\ 0 & 0 & -I \end{bmatrix}, \quad (12)$$

in which A_k and B_k are the sensitivities of the equality constraints, $b(p)$, with respect to the states and inputs. They are

$$A_k = \nabla_{x_k} F_k(x_k, u_k, d_k), \quad (13a)$$

$$B_k = \nabla_{u_k} F_k(x_k, u_k, d_k). \quad (13b)$$

3.2 Interior point algorithm

We use a structured primal-dual interior point algorithm for the solution of the constrained QP (10). In this algorithm, we implement a Riccati recursion to compute the Newton iterations in the primal-dual interior point algorithm (Rao et al. (1998); Jørgensen et al. (2004); Boiroux (2012)). This Riccati recursion exploits the structure of the Hessian of the Lagrangian (28) and the gradients of the equality constraints (12). The computation time of this procedure scales linearly with the prediction horizon, whereas the computational time of classical matrix factorization techniques grows as $O(N^3)$. This factorization can be used to compute the optimal variation in the manipulated variables Δu_k , the optimal change in states variables Δx_{k+1} , and the Lagrange multipliers, y_{k-1} (Jørgensen (2005)). For many OCPs with long control and prediction horizon, N , Riccati recursion-based interior point solvers are considered as the most computationally efficient method to solve the QP sub-problem (10) (Jørgensen et al. (2012); Frison and Jørgensen (2013); Hagdrup et al. (2017)).

The equality constraints (10b) can be rewritten as

$$\Delta x_{k+1} = A'_k \Delta x_k + B'_k \Delta u_k + \Delta v_k - \Delta w_k + b_k, \quad (14)$$

for $k = 0, 1, \dots, N$, or equivalently

$$\Delta x_{k+1} = A'_k \Delta x_k + \tilde{B}'_k \Delta \tilde{u}_k + b_k, \quad (15)$$

where

$$\tilde{B}_k = [B_k \ I \ -I]', \quad \tilde{u}_k = [u_k \ v_k \ w_k]'. \quad (16)$$

By using this convention, it is possible to use a Riccati recursion algorithm to solve (10).

3.3 Second order correction

The second order correction (SOC) avoids the Maratos effect (Maratos (1978)), i.e. a loss of the superlinear convergence. A similar effect may happen to trust region algorithms, as explained in the work by Yuan (1984). The SOC algorithm is described in Exler and Schittkowski (2007). The objective function for the SOC is

$$\phi_c = \frac{1}{2} p'_c H p_c + (g + H p_k)' p_c + \mu \sum_{i \in \mathcal{E}} (v_{c,i} + w_{c,i}) + \mu \sum_{i \in \mathcal{I}} t_{c,i}. \quad (17)$$

It requires the solution of the following QP for the correction step, p_c ,

$$\min_{p_c, v_c, w_c, t_c} \phi_c \quad (18a)$$

$$s.t. \quad \nabla b(\tilde{x}_k)'(p_k + p_c) + w_c - v_c = -b(\tilde{x}_k + p_k) \quad (18b)$$

$$\nabla c(\tilde{x}_k)' p_c \geq -c(\tilde{x}_k + p_k) - t_c \quad (18c)$$

$$v_c + v_k, w_c + w_k, t_c + t_k \geq 0 \quad (18d)$$

$$-\Delta \leq p_k + p_c \leq \Delta \quad (18e)$$

The QP (18) requires the evaluation of the equality constraints, inequality constraints, but does not require an update of the sensitivities.

3.4 Computation of the merit function

The ℓ_1 merit function is

$$\phi_1(\tilde{x}, \mu) = f(x) + \mu \sum |b(\tilde{x})| + \mu \sum \max(c(\tilde{x}), 0). \quad (19)$$

The estimated approximation of the objective function, $q_\mu(p)$, is

$$q_\mu(p) = f_k + \nabla f'_k p + \frac{1}{2} p' B_k p + \mu \sum |b(x_k) + \nabla b(\tilde{x}_k)' p| + \mu \sum \max(-\nabla c(\tilde{x}_k)' p - d, 0). \quad (20)$$

To accept or reject a step p_k , we evaluate the ratio

$$\rho = \frac{a_{red}}{p_{red}} = \frac{\phi_1(\tilde{x}_k, \mu) - \phi_1(\tilde{x}_k + p_k, \mu)}{q_\mu(0) - q_\mu(p_k)}. \quad (21)$$

The numerator describes the actual reduction (or increase) in the merit function between the initial point \tilde{x}_k and the new iterate $\tilde{x}_k + p_k$. The denominator is the estimated decrease in the merit function. Thus, the ratio (21) compares the actual reduction in the objective function, a_{red} , with the reduction predicted by the model, p_{red} . It monitors the accuracy of the second order approximation of the NLP in the trust region and ensures the global convergence of the trust-region algorithm. We accept the step $\tilde{x}_k + p_k$ if $\rho > 0$, and reject it otherwise.

3.5 Update of the trust region

If the current step is accepted, we want to increase or reduce the size of the trust region depending on ρ

$$\Delta_{k+1} = \gamma(\rho) \Delta_k. \quad (22)$$

If the current step is rejected, we would like to shrink the trust region

$$\Delta_{k+1} = \gamma(\rho) \|p\|_\infty. \quad (23)$$

If ρ is greater than 0.5, we assume that our model is accurate enough to represent the NLP, and therefore we increase the size of the trust region to allow larger steps. Conversely, if $\rho < 0.5$, it means that the QP is not accurate enough, and we reduce the size of the trust region to avoid rejected steps. To ensure smooth variations on Δ , we use the following function to compute $\gamma(\rho)$

$$\gamma(\rho) = \min(\max((2\rho - 1)^3 + 1, 0.25), 2). \quad (24)$$

Fig. 1 depicts $\gamma(\rho)$ and compares it with the classical update

$$\begin{cases} \gamma = 0.25, & \rho < 0.25, \\ \gamma = 1, & 0.25 \leq \rho \leq 0.75, \\ \gamma = 2, & \rho > 0.75. \end{cases} \quad (25)$$

3.6 Update of penalty parameter

At each iteration, we want to update the ℓ_1 penalty parameter, μ . If the equality and/or inequality constraints are not satisfied, we want to increase μ to make sure that the equality and inequality constraints are satisfied whenever possible. On the other hand, the algorithm must ensure that μ is not too large to avoid taking too small steps. Thus, if the equality and/or inequality constraints are not satisfied, we increase μ by setting

$$\mu_{k+1} = \min(2\mu_k, \bar{\mu}). \quad (26)$$

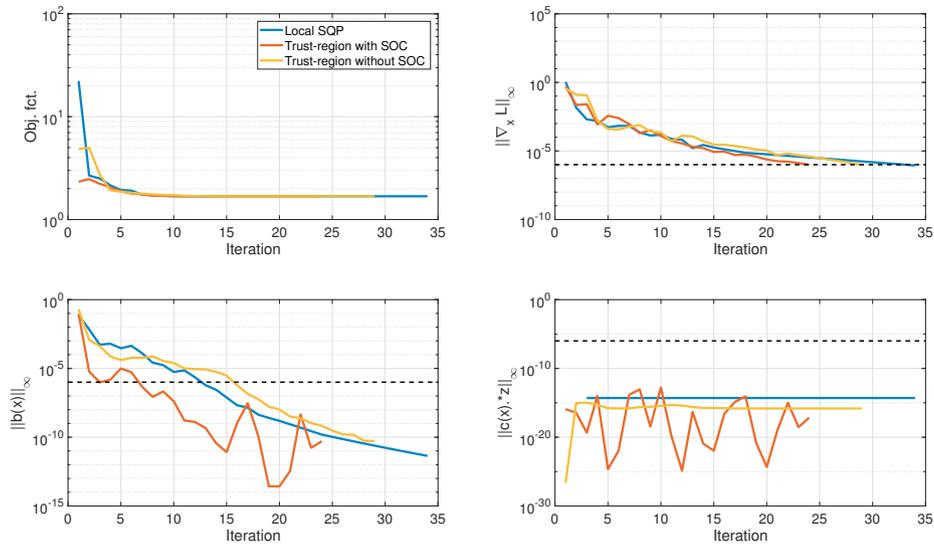


Fig. 3. Objective function value (top left), gradient of the Lagrangian norm (top right), equality constraints norm (bottom left) and complementarity condition norm (bottom right) for the Van der Pol oscillator.

$$\begin{aligned} \phi = & \frac{1}{2} \int_0^5 (x_1^2(t) + x_2^2(t) + u^2(t)) dt \\ & + \frac{\eta}{2} (x_1(5) - x_2(5) + 1)^2. \end{aligned} \quad (32)$$

and the dynamics are described by the following ODEs

$$\dot{x}_1(t) = x_2(t), \quad (33a)$$

$$\dot{x}_2(t) = -x_1(t) + \alpha(1 - x_1^2)x_2 + u(t). \quad (33b)$$

For the simulations, we set $\eta = 100$ and $\alpha = 1$. We set the bound constraints, u_{\min} and u_{\max} , to -1 and 1 , respectively. The tolerance requirements are set to 10^{-6} . The initial condition is $x(0) = [1; 0]$.

Fig. 2 depicts the state vector, $x(t)$, and the input, $u(t)$. The shape of the solution is similar to the optimal states and inputs in Bock and Plitt (1984).

Fig. 3 shows the objective function, the gradient of the Lagrangian norm (8a), the equality constraints norm (8b), and the complementarity condition norm (8e). We compare between our trust-region algorithm with SOC, our trust-region algorithm without SOC and a previously published local SQP algorithm with line search (Boiroux et al. (2010)). For the Van der Pol problem, the local SQP algorithm converges more slowly than the trust region-based algorithms. Also, adding the SOC makes the convergence even faster for the equality constraints.

Table 1 shows the number of SQP iterations, the total number of model evaluations and the total number of sensitivity evaluations for different problem sizes. As for the multiple shooting algorithm presented in Bock and Plitt (1984), the number of SQP iterations does not increase with the prediction and control length.

Fig. 4 shows the CPU times of an implementation of this trust-region algorithm for different control and prediction horizons. We implemented a prototype of our trust-region algorithm in Matlab 2017a. The computational burden scales linearly for the solution of the QP subproblem

Table 1. Number of SQP iterations, model evaluations and sensitivity evaluations for different control and prediction horizon lengths, N .

N	SQP iterations	Model evaluations	Sensitivity evaluations
10	13	8855	7805
25	27	18277	18235
30	13	7413	7406
40	17	10136	10136
60	27	23520	23520
80	28	32480	32480
100	28	40600	40600

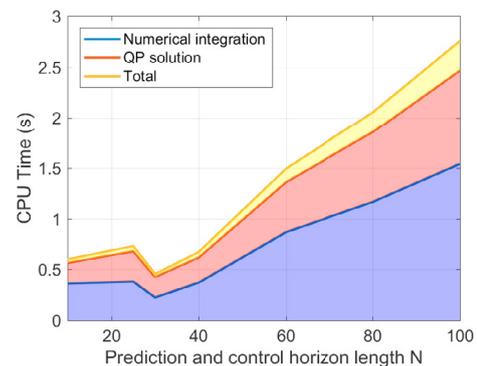


Fig. 4. CPU times for different prediction and control horizons.

and the numerical integration/sensitivity computation. For $N = 100$, it takes approximately 60% of the total computation time, whereas the interior point algorithm takes approximately 25% of the computation time.

5. CONCLUSION

In this paper, we developed and tested a trust-region algorithm for the solution of OCPs. The algorithm ex-

exploits the sparsity and the structure of the OCP. Second order correction accelerates the convergence, especially of the nonlinear equality constraints. The Riccati recursion becomes particularly computationally efficient when the number of states is small relatively to the prediction horizon. In particular, the complexity scales linearly with the prediction horizon length. Compared to the Matlab prototype, a C implementation of the SQP algorithm and warm-start strategies in closed-loop would significantly decrease the computational time.

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