

Moment and SDP relaxation techniques for smooth approximations of nonlinear differential equations

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March 9, 2010

Abstract

Combining recent moment and sparse semidefinite programming (SDP) relaxation techniques, we propose an approach to find smooth approximations for solutions of nonlinear differential equations. Given a system of nonlinear differential equations, we apply a technique based on finite differences and sparse SDP relaxations for polynomial optimization problems (POP) to obtain a discrete approximation of its solution. In a second step we apply maximum entropy estimation (using moments of a Borel measure associated with the discrete solution) to obtain a smooth closed-form approximation. The approach is illustrated on a variety of linear and nonlinear ordinary differential equations (ODE) and partial differential equations (PDE) and preliminary numerical results are reported.

1 Introduction

Problems involving nonlinear differential equations arise in a variety of models for real world problems. Even finding *approximate* solutions for nonlinear differential equations remains a challenge. In a previous work [8, 9] we have established a technique based on sparse semidefinite programming (SDP) relaxations to detect discrete approximations for solutions of systems of nonlinear differential equations. In this paper we present a novel approach to obtain smooth approximations for solutions of differential equations. Namely, an approximate solution is obtained by applying maximum entropy estimation [3, 6] with a finite number of moments of a Borel measure associated with a discrete approximation of the solution of the differential equation. For *linear* differential equations, an SDP relaxation based method was proposed in [1] to generate contracting sequences of lower and upper bounds for the moments.

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Our contribution in this paper is primarily concerned with *nonlinear* differential equations. In a first step, we take advantage of the discrete approximations provided by the SDP relaxation method in [8] to compute a finite set of moments for an appropriately defined measure with discrete support. Next, an approximation for the solution of the differential equation is obtained in closed form by maximum entropy estimation, using the moments of the discrete measure. To the best of our knowledge, it seems to be the first attempt to apply maximum entropy estimation to obtain smooth approximations for solutions of linear and nonlinear differential equations. Finally, if maximum entropy estimation does guarantee some weak convergence of the estimate to the true solution as the number of moments increases, it does not guarantee *pointwise* convergence on the entire domain of the differential equation. However, as our preliminary results show for different linear and nonlinear differential equations, accurate pointwise approximations can be achieved on certain regions of the domain.

The structure of the paper is as follows. In Section 2 we briefly recall the sparse SDP relaxations method for solving nonlinear differential equations numerically, which is the basis for our technique. In Section 3 we introduce the method of maximum entropy estimation. Our technique to compute smooth approximations for the solutions of ordinary differential equations (ODE) and partial differential equations (PDE), which combines the methods from Section 2 and 3, is presented in Section 4. Finally, preliminary numerical results for this method are reported in Section 5.

2 Sparse SDP relaxations for solving differential equations

In this section we recall the approach to compute discrete approximations for solutions to systems of differential equations with polynomial data presented in [8].

2.1 Transforming a differential equation into a POP

In this paper we consider bidimensional differential equation problems of the following type

$$\begin{aligned} L(u(x, y)) + G(u(x, y)) &= f(x, y) \quad \forall (x, y) \in \Omega, \\ H(u(x, y)) &= g(x, y) \quad \forall (x, y) \in \partial\Omega, \\ \text{lbd} &\leq u(x, y) \leq \text{ubd} \quad \forall (x, y) \in \Omega, \end{aligned} \tag{1}$$

with $\Omega := [x_{\min}, x_{\max}] \times [y_{\min}, y_{\max}] \subset \mathbb{R}^2$, $f : \Omega \rightarrow \mathbb{R}^m$, $g : \partial\Omega \rightarrow \mathbb{R}^m$ smooth functions, $L : \mathcal{D} \rightarrow \mathcal{D}$ and $H : \mathcal{D} \rightarrow \mathcal{D}$ differential operators, $G : \mathcal{D} \rightarrow \mathcal{D}$ operator, L , H and G are polynomial in the function $u \in \mathcal{D}$ and its derivatives for some function space $\mathcal{D} \subseteq L_1(\Omega)$, with $L_1(\Omega)$ the Banach space of integrable functions on Ω , and $\text{lbd} < \text{ubd}$ bounds for the function values of u .

In a first step of the sparse semidefinite programming relaxation (SDPR) method for solving differential equations, we transform an ODE or a PDE of form (1) into a polynomial optimization problem (POP). We then discretize the rectangular domain Ω by N (one-dimensional case) or $N_x N_y$ (two-dimensional case) grid points, approximate the derivatives by standard finite differences, for instance $\frac{\partial^2 u(x_i, y_j)}{\partial x^2} \approx \frac{u_{i+1,j} - 2u_{i,j} + u_{i-1,j}}{\Delta x^2}$, where $u_{i,j} := u(x_i, y_j)$, and denote

the discretized differential operators at some interior grid point (x_i, y_j) and boundary grid point (x_k, y_l) as $L_{i,j}$ and $H_{k,l}$, respectively. Finally, we take the discretization of the problem (1) as a system of constraints, choose some objective function F which needs to be polynomial in u , i.e. $F(u) \in \mathbb{R}[u]$, and obtain the following optimization problem

$$\begin{aligned} \min & F(u) \\ \text{s.t.} & L_{i,j}(u) + G(u_{i,j}) = f(x_i, y_j), \\ & \text{lbd}_{i,j} \leq u_{i,j} \leq \text{ubd}_{i,j} \quad \forall (i, j) \in \{1..N_x\} \times \{1..N_y\}, \\ & H_{k,l}(u) = g(x_k, y_l) \quad \forall (k, l) \in \{1, N_x\} \times \{1..N_y\} \cup \{1..N_x\} \times \{1, N_y\} \end{aligned} \quad (2)$$

which, since all functions are polynomial in the variable $u = (u_{1,1}, \dots, u_{N_x, N_y})$, is a POP.

2.2 Sparse SDP relaxations

Problem (2) is of the form:

$$\begin{aligned} \text{POP} \quad \min & F(u) \\ \text{s.t.} & \tilde{g}_j(u) \geq 0 \quad \forall j \in \{1, \dots, k\}, \\ & \tilde{h}_i(u) = 0 \quad \forall i \in \{1, \dots, l\}, \\ & \text{lbd}_s \leq u_s \leq \text{ubd}_s \quad \forall s \in \{1, \dots, \tilde{n}\}, \end{aligned} \quad (3)$$

where $F(u) = \sum_{\alpha \in \mathbb{N}^{\tilde{n}}} F_\alpha u^\alpha$, $\tilde{g}_j(u) = \sum_{\alpha \in \mathbb{N}^{\tilde{n}}} g_{j\alpha} u^\alpha$ and $\tilde{h}_i(u) = \sum_{\alpha \in \mathbb{N}^{\tilde{n}}} h_{i\alpha} u^\alpha$. As mentioned above, the dimension of this POP is $\tilde{n} = N_x N_y$ (or $\tilde{n} = N$ in the 1-dimensional case). But due to the structure of the finite difference discretization only a small number of the \tilde{n} components of u occurs in each constraint or in each monomial of the objective function of (2). Thus, the POP derived from nonlinear differential equations are sparse.

A systematic way of characterizing the structured sparsity of a POP has been introduced in [11], and the structured sparsity is exploited by the *sparse SDP relaxations* in [11]. For the POP (3) one obtains the sparse SDP relaxations:

$$\begin{aligned} \text{SDP}_w \quad \min & \sum_{|\alpha| \leq 2w} F_\alpha y_\alpha \\ \text{s.t.} & M_{w-w_j}(\tilde{g}_j y, I_{t(j)}) \succcurlyeq 0 \quad \forall j \in \{1, \dots, k\} \\ & M_{w-\tilde{w}_i}(\tilde{h}_i y, I_{\tilde{t}(i)}) = 0 \quad \forall i \in \{1, \dots, l\} \\ & M_w(y, I_t) \succcurlyeq 0 \quad \forall t \in \{1, \dots, d\} \\ & \text{lbd}_s \leq y_s \leq \text{ubd}_s \quad \forall s \in \{1, \dots, \tilde{n}\}, \end{aligned} \quad (4)$$

where $w_j := \lceil \frac{\deg \tilde{g}_j}{2} \rceil$, $\tilde{w}_i := \lceil \frac{\deg \tilde{h}_i}{2} \rceil$, $\{I_t\}_{t=1}^d$ is the set of subsets of $\{1, \dots, \tilde{n}\}$ derived from the correlative sparsity pattern matrix of the POP [11], $M_w(\cdot, \cdot)$ and $M_{w-w_j}(\cdot, \cdot)$ are the partial moments and localizing matrices [5], and $w \geq w_{\min} := \max_{i,j} (w_j, \tilde{w}_i)$ is the order of the SDP relaxation. As w increases, solving SDP_w generates a nondecreasing sequence of lower bounds for $\min(\text{POP})$, namely:

$$\min(\text{SDP}_{w_{\min}}) \leq \min(\text{SDP}_{w_{\min}+1}) \leq \dots \leq \min(\text{POP}).$$

Moreover, if (3) has a unique minimizer x^* , the vector $(y_{w,1}^*, \dots, y_{w,\tilde{n}}^*)$ obtained from an optimal solution y_w^* of (4) is an approximation of x^* , and under certain compactness conditions [5], as $w \rightarrow \infty$,

$$\min(\text{SDP}_w) \rightarrow \min(\text{POP}) \quad \text{and} \quad y_w^* \rightarrow x^*. \quad (5)$$

2.3 Discrete approximation

From (5), asymptotic convergence of minimum and minimizer of SDP_w to minimum and minimizer of POP (3) are guaranteed under uniqueness of the optimal solution and compactness of the feasible set of the POP. However, recall that the dimension \tilde{n} of POP (3) is $N_x N_y$, and so, if w is much larger than w_{\min} , the resulting SDP_w in (4) is untractable for general purpose SDP solvers. Therefore, we have to restrict ourselves to $w \in \{w_{\min}, w_{\min} + 1\}$ for medium scale N , and we cannot expect that $\text{SDP}_{w_{\min}}$ or $\text{SDP}_{w_{\min}+1}$ provide accurate approximations to a solution of a nonlinear differential equation. In order to improve accuracy, we may apply additional locally convergent optimization techniques. For instance sequential quadratic programming (SQP) can be applied to (2), starting from the solution of SDP_w as initial guess. Combining the sparse SDP relaxation with SQP (or another local method) is summarized in the scheme:

Method 1 *The SDPR method*

1. Choose a discretization (N_x, N_y) for the differential equation problem.
2. Choose a relaxation order w and an objective function. Apply SDP_w to (2) and obtain its solution \tilde{u} and the lower bound $\min(\text{SDP}_w)$ for $\min(\text{POP})$.
3. Apply sequential quadratic programming (SQP) to (2) with \tilde{u} as initial guess, and obtain u as discrete approximation to a solution of the differential equation problem.

3 Maximum entropy estimation

In this section we briefly introduce the *maximum entropy estimation* [3, 6, 7], our second tool to find smooth approximations for solutions of nonlinear differential equations. The maximum entropy estimation is concerned with the following problem: Let $u \in L_1(\Omega)$ be nonnegative and partially known by the finite vector m of moments up to order M of the associated Borel measure $d\mu := u dx dy$ on Ω . From the only knowledge of m , find an estimate $u_M \in L_1(\Omega)$ such that all moments of order up to M of the measure $d\mu_M := u_M dx dy$ match those of $d\mu$ and analyze the asymptotic behavior of u_M as $M \rightarrow \infty$. An elegant method consists in finding the estimate u_M that maximizes the *Boltzmann-Shannon* entropy functional

$$u \mapsto \int_{\Omega} u \ln u dx dy, \quad u \in L_1(\Omega).$$

In this case, the optimal estimate u_M^* is given by

$$u_M^*(v^*, x, y) = \exp \sum_{\substack{0 \leq i, j \leq M \\ i+j \leq M}} v_{i,j}^* x^i y^j, \quad (6)$$

where $v^* \in \mathbb{R}^{|m|}$ is a (global) optimizer of the *convex* finite-dimensional optimization problem:

$$\max_{v \in \mathbb{R}^{|m|}} \langle m, v \rangle - \int_{\Omega} u_M(v, x, y) dx dy. \quad (7)$$

The optimization problem (7) can be solved by first or second order methods like Newton's method or SQP. For these methods, gradient and Hessian of the objective function in (7) must be computed. In the case the domain Ω is simple, we may compute them by quadrature and cubature formulas. For more difficult domains one may use the procedure described in [6, 2]. Concerning the behavior of u_M^* as $M \rightarrow \infty$ and its relationship with u , one has the following weak convergence result from [3].

Proposition 1 *Let u_M^* be obtained from an optimal solution of (7). Then, as $M \rightarrow \infty$,*

$$\int_{\Omega} \psi(x, y) u_M^*(x, y) dx dy \rightarrow \int_{\Omega} \psi(x, y) u(x, y) dx dy,$$

for every bounded measurable function $\psi : \Omega \rightarrow \mathbb{R}$ which is continuous almost everywhere.

However, the *pointwise* convergence $u_M^*(x, y) \rightarrow u(x, y)$ does not hold in general.

4 Smooth approximations to solutions of differential equations

In this section we show how to combine the SDPR method and maximum entropy estimation to obtain smooth approximations for solutions of linear and nonlinear differential equations. Our discussion focuses on the 2-dimensional case, but the 1-dimensional case is covered analogously. Let $u \in \mathcal{D}$ be a solution of (1) and assume without loss of generality that $\text{lbd} \geq 0$ so that u is nonnegative on Ω . For $\text{lbd} < 0$ define $\tilde{u} := u - \text{lbd}$ and apply the outlined procedure to the new function \tilde{u} . Associated with u , let $d\mu(x, y) := u dx dy$ be the finite Borel measure on Ω with moment vector $m = (m_{i,j})$ of all moments up to order M :

$$m_{i,j} := \int_{\Omega} x^i y^j d\mu(x, y) = \int_{\Omega} x^i y^j u(x, y) dx dy,$$

for $(i, j) \in \mathbb{N}^2$ with $i + j \leq M$. For linear PDEs, a hierarchy of tightening lower and upper bounds for the components $m_{i,j}$ of the moment vector can be obtained by solving a sequence of SDP as proposed in [1]. However, this approach cannot be applied in the case of nonlinear PDE. Our strategy is to use a discrete approximation $(u_{k,l})_{1 \leq k \leq N_x, 1 \leq l \leq N_y}$ of a solution of the PDE to approximate the moments $m_{i,j}$ by:

$$m_{i,j}^{\Delta} = \sum_{k=1}^{N_x} \sum_{l=1}^{N_y} x_k^i y_l^j u_{k,l} \Delta x \Delta y, \quad (8)$$

for $(i, j) \in \mathbb{N}^2$ with $i + j \leq M$. If the discretization (N_x, N_y) is sufficiently fine and $(u_{k,l})_{k,l}$ is a close approximation of u , then we expect $m_{i,j}^{\Delta}$ to be a good approximation of $m_{i,j}$ for all $(i, j) \in \mathbb{N}^2$. Thus, we can apply maximum entropy estimation to the vector m^{Δ} to obtain a smooth approximation of u . This idea is formalized in the following algorithm for obtaining smooth approximations of solutions of linear or nonlinear PDE problems.

Method 2 *The smooth SDP approximation method*
Given a PDE problem of form (1).

1. Choose a discretization (N_x, N_y) , relaxation order w and objective F , and apply the SDPR method to obtain a discrete approximation $(u_{k,l})_{k,l}$ to a solution of the PDE problem. If not given in the formulation of the PDE problem, impose lower and upper bounds, lbd and ubd for u .
2. Choose a moment bound $M \in \mathbb{N}$ and use $(u_{k,l})_{k,l}$ to calculate m^Δ as in (8).
3. Apply maximum entropy estimation to m^Δ and obtain vector $v^* \in \mathbb{R}^{|m^\Delta|}$, optimal solution of (7).
4. Obtain the approximation u_M with $u_M(x, y) = \sum_{i,j} \exp(v_{i,j}^* x^i y^j)$ for a solution u of the PDE problem (1) on Ω .

As $M \rightarrow \infty$, $u_M \rightarrow u$ weakly (see Proposition 1) but not pointwise, i.e., one cannot guarantee $u_M(x, y) \rightarrow u(x, y)$ on Ω . Nevertheless, as reported in [6] the maximum entropy estimation may provide accurate pointwise approximation of the unknown function to be recovered on certain segments of the domain Ω . We next illustrate on a variety of PDE problems, that indeed good pointwise approximation can be obtained on some parts of the domain Ω .

5 Numerical Experiments

We illustrate the potential of Method 2 on a variety of ODE and PDE problems. As an implementation of the sparse SDP relaxations we apply the software SparsePOP [12] and as an implementation of sequential quadratic programming (SQP) in the SDPR method and in solving the optimization problem (7) we apply the Matlab Optimization Toolbox commands *fmincon* and *fminunc*, respectively. As we restrict ourselves to ODE and PDE with rectangular domains Ω we can apply standard quadrature and cubature formulas to compute the gradient and Hessian for (7). Thus, we apply the Matlab commands *trapz* in the one-dimensional case and *dblquad* in the two-dimensional case, respectively. In order to evaluate the quality of the smooth approximation provided by Method 2 we define the *average error* $\bar{\epsilon}_u(M) := \Delta x \sum_i u(x_i) - u_M^*(x_i)$ and the *maximum pointwise error* $\epsilon_u^{\max}(M) := \max_i |u(x_i) - u_M^*(x_i)|$.

5.1 Linear differential equations

As first test problems for our approach we consider a linear ODE and a linear PDE from [1] and compare (a) the discretized moment approximations obtained by Method 2 to the bounds obtained in [1], and (b) the smooth approximation u_M^* to the known analytic solution.

Linear ODE The linear ODE is given by,

$$\begin{aligned} u''(x) + 3u'(x) + 2u(x) &= 0 \quad \forall x \in [0, 1], \\ u'(0) &= -2e^2, \quad u'(1) = -2. \end{aligned} \tag{9}$$

For this problem the unique solution is $u(x) = e^2 e^{-2x}$. We apply Method 1 with $F = -\sum_i u_i$, $N = 2000$ and $w = 1$. We calculate the approximate moments m^Δ for $M = 40$ and compare

i	m_i^Δ	$m_i^{[1]}$
0	3.1942	3.1945
1	1.0957	1.0973
10	0.1086	0.1088
20	0.0524	0.0524
30	0.0345	0.0344
40	0.0258	0.0256

Table 1: Approx. moments m^Δ for $N = 2000$ compared to approx. $m^{[1]}$ derived from lower and upper bounds in [1] for (9)

M	1	2	3	4	5
v_0^*	2.0043	2.0042	2.0040	2.0032	2.0039
v_1^*	-2.0135	-2.0083	-1.9922	-1.9744	-1.9528
v_2^*		-0.0083	-0.0938	-0.1998	-0.3205
v_3^*			0.0851	0.2886	0.3269
v_4^*				-0.1180	0.2018
v_5^*					-0.2694
$\bar{\epsilon}_u(M)$	0.0042	0.0044	0.0042	0.0039	0.0044
$\epsilon_u^{\max}(M)$	0.0242	0.0228	0.0228	0.0222	0.0326

Table 2: Smooth SDP approx. for linear ODE (9)

them to approximate moments for m derived in [1] by contracting lower and upper bounds in Table 1. All moments coincide up to the fourth digit.

We apply Method 2 for $M \in \{1, \dots, 5\}$ and report the resulting vector v_M^* in Table 2.

Note that the actual solution of the ODE problem corresponds to a parameter vector $v_{\text{opt}} = (2, -2, 0, \dots)$. As reported in Table 2, $(v_0^*(M), v_1^*(M)) \approx (2, -2)$, and even though $v_i^*(M) \neq 0$ for $i > 1$, the maximum pointwise error is quite small.

Linear PDE The linear PDE is given by

$$u_{xx}(x, y) + u_{yy}(x, y) - 3e^{x+y} = 0 \quad \forall (x, y) \in [0, 1]^2, \quad (10)$$

where the boundary conditions are set up such that $u(x, y) = e^{x+y}$ is the unique solution of the PDE problem. We apply the SDPR method with $F(u) = -\sum_{k,l} u_{k,l}$, $w = 1$ and $N_x = N_y = 100$, compute m^Δ for all moments of order up to 3 and compare these moments to the exact moments derived from the known solution and to the best lower and upper bounds for the moments from Table 7 in [1]. See Table 3 for the results. Our approach provides some approximations for the moments that is well within the bounds LB and UB from [1].

Also for this problem, there is a vector $v_{\text{opt}} = (0, 1, 1, 0, \dots)$ corresponding to the solution u . When applying Method 2 with $M \in \{2, 3\}$ we obtain $v^*(M)$ reported in Table 4 with errors $\bar{\epsilon}_u(2) = 0.0677$, $\bar{\epsilon}_u(3) = 0.0682$, $\epsilon_u^{\max}(2) = 1.0276$ and $\epsilon_u^{\max}(3) = 1.3267$.

For both linear differential equations we obtain accurate approximations of the moments for

(i, j)	$m_{i,j}^\Delta$	$m_{i,j}$	LB	UB
(0,0)	2.9512	2.9525	2.9235	3.1707
(1,0)	1.7287	1.7183	1.6944	1.7742
(1,1)	1.0121	1.0000	0.9847	1.0130
(2,0)	1.2504	1.2342	1.1123	1.3088
(2,1)	0.7319	0.7183	0.7151	0.7458
(2,2)	0.5292	0.5159	0.4948	0.5456
(3,0)	0.9869	0.9681	0.8244	1.0478
(3,1)	0.5775	0.5634	0.5054	0.5818
(3,2)	0.4176	0.4047	0.3874	0.5818
(3,3)	0.3295	0.3175	0.3017	0.3399

Table 3: Approx. moments for $N_x = N_y = 100$ compared to exact moments and bounds from [1] for linear PDE (10)

(i, j)	(0,0)	(1,0)	(0,1)	(2,0)	(1,1)	(0,2)
$v_{i,j}^*(2)$	0.064	0.709	0.710	0.329	0.099	0.329
$v_{i,j}^*(3)$	0.013	0.959	0.959	-0.213	0.160	-0.213
$v_{\text{opt}i,j}$	0	1	1	0	0	0

Table 4: Smooth SDP approx. for linear PDE (10)

the measures associated with the unique solutions. Moreover, unlike [1], we can exploit these moment approximation to find smooth approximations for the actual solutions.

5.2 A nonlinear elliptic PDE

As a first nonlinear problem, consider the elliptic PDE:

$$\begin{aligned}
u_{xx} + u_{yy} + 22u(1 - u^2) &= 0 && \text{on } [0, 1]^2, \\
u &= 0 && \text{on } \partial[0, 1]^2, \\
0 \leq u \leq 1 &&& \text{on } [0, 1]^2.
\end{aligned} \tag{11}$$

This problem is well known to have a nontrivial positive solution. We apply Method 2 with $F(u) := -\sum_{k,l} u_{k,l}$, $w = 2$, $N_x = N_y = 49$ and $M \in \{2, 3\}$, and obtain an accurate discrete approximation $(u_{i,j})_{i,j}$ and two smooth approximations u_2^* and u_3^* with errors $(\epsilon_u^{\max}(2), \bar{\epsilon}_u(2)) = (0.081, -0.002)$ and $(\epsilon_u^{\max}(3), \bar{\epsilon}_u(3)) = (0.076, -0.002)$, respectively. In Figure 1 it is illustrated how accurate the smooth approximation u_3^* resembles the shape of the discrete approximation $(u_{i,j})_{i,j}$.

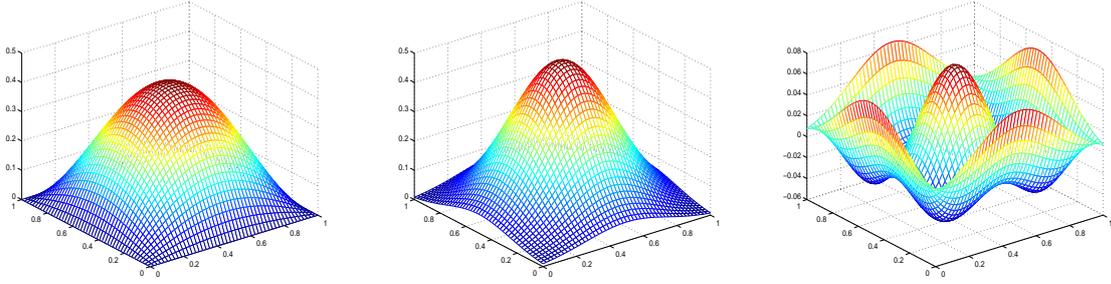


Figure 1: Discrete approx. (left), smooth approx. (center) for the same grid, and pointwise difference between the two (right) for nonlinear PDE (11)

5.3 Reaction diffusion equation

A challenging ODE problem which is known to have many solutions [10] is given by :

$$\begin{aligned}
 \frac{1}{20} u'' + \frac{1}{9} (35 + 16u - u^2) u - uv &= 0 \text{ on } [0, 5], \\
 4v'' - \left(1 + \frac{2}{5}v\right) v + uv &= 0 \text{ on } [0, 5], \\
 u'(0) = u'(5) = v'(0) = v'(5) &= 0, \\
 0 \leq u, v \leq 14 & \text{ on } [0, 5].
 \end{aligned} \tag{12}$$

To ensure numerical stability we scale the domain $[0, 5]$ of (12) to $[0, 1]$ before applying Method 2, as $\exp(x^i)$ gets very large for $|x| > 1$. Problem (12) involves two functions u and v , thus we need to apply Method 2 twice, once for u and once for v , in order to obtain smooth approximations for both functions. Note that the SDPR method only needs to be applied once and provides a discrete approximation $(u_i, v_i)_i$, maximum entropy estimation needs to be applied twice. We apply Method 2 for $F(u, v) = -u \frac{N}{2}$, $N = 100$, $w = 3$ and $M \in \{10, 20, 30, 50\}$. Solutions for u and v and the derived smooth approximations are pictured in Figure 2 and the errors are reported in Table 5. Even though the average and the maximum pointwise approximation errors are not small, even for large M , we observe that the pointwise approximation gets more and more accurate on certain segments of the domain - in this case the third part of the interior, where the third peak of u and v occurs. The pointwise approximation is not good - or does even get worse - near the boundary of $[0, 1]$.

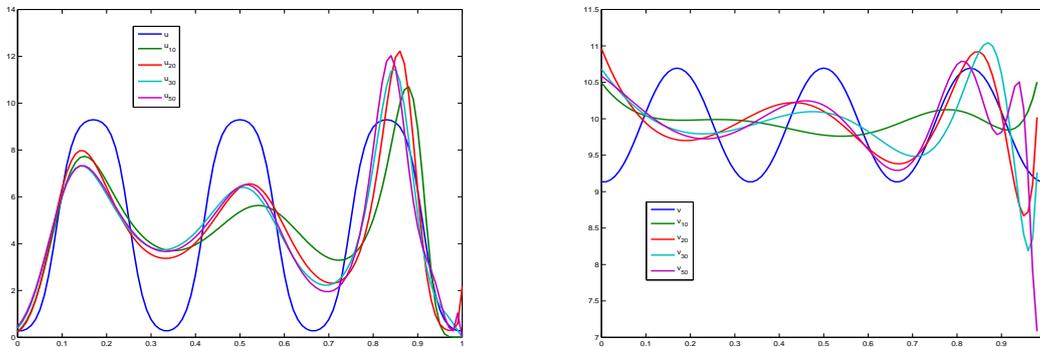


Figure 2: Smooth approx. for u (left) and v (right) for $M \in \{10, 20, 30, 50\}$ for nonlinear ODE (12)

M	$\epsilon_u^{\max}(M)$	$\bar{\epsilon}_u(M)$	$\epsilon_v^{\max}(M)$	$\bar{\epsilon}_v(M)$
10	4.11	0.0011	2.10	0.1080
20	3.84	0.0143	6.66	0.1371
30	3.48	0.0012	9.61	0.1547
50	3.39	0.0085	23.69	0.2658

Table 5: Errors for nonlinear ODE (12)

5.4 Coupled nonlinear, elliptic PDE

In this example we consider a system of two PDE in two unknown functions u and v :

$$\begin{aligned}
u_{xx} + u_{yy} + u(1 - u^2 - v^2) &= 0 && \text{on } [0, 1]^2, \\
v_{xx} + v_{yy} + v(1 - u^2 - v^2) &= 0 && \text{on } [0, 1]^2, \\
0 \leq u, v &\leq 5 && \text{on } [0, 1]^2.
\end{aligned} \tag{13}$$

We consider two alternative sets of boundary conditions: Dirichlet conditions given by

$$\begin{aligned}
u(0, y) &= 0.5y + 0.3 \sin(2\pi y), & u(1, y) &= 0.4 - 0.4y, \\
u(x, 0) &= 0.4x + 0.2 \sin(2\pi x), & u(x, 1) &= 0.5 - 0.5x, \\
v(x, 0) &= v(x, 1) = v(0, y) = v(1, y) = 0
\end{aligned} \tag{14}$$

for $x, y \in [0, 1]$, and Neumann conditions given by

$$\begin{aligned}
u_x(0, y) &= -1, & u_x(1, y) &= 1, \\
u_y(x, 0) &= 2x, & u_y(x, 1) &= x + 5 \sin\left(\frac{\pi x}{2}\right), \\
v_x(0, y) &= 0, & v_x(1, y) &= 0, \\
v_y(x, 0) &= -1, & v_y(x, 1) &= 1,
\end{aligned} \tag{15}$$

for $x, y \in [0, 1]$. We apply Method 2 with $F(u, v) = -\sum_{i,j} u_{i,j}$, $w = 2$, $N_x = N_y = 33$ for both settings (14) and (15) of boundary conditions for (13). Numerical results for approximation of the function u for boundary conditions (14) and (15) can be found in Table 6 and Table 7, respectively. We make two observations. On the one hand, increasing M does neither improve the average nor the maximum pointwise approximation error. Although one has to keep in mind that we apply Method 2 for relatively small choices of M , such that SDP or SQP solvers can tackle the subproblems in Method 2 within several minutes of computation time. On the other hand, both errors $\bar{\epsilon}_u(M)$ and $\epsilon_u^{\max}(M)$ are significantly smaller if we do not consider u_M^* near the boundary. Thus, (u_M^*, v_M^*) provides an accurate smooth approximation to a solution (u, v) of the PDE problem on the interior of the domain $[0, 1]^2$. We illustrate this behavior for u_M^* in the case of (14) in Figure 3. Maximum pointwise and average approximation errors are reported in Tables 6 and 7 on three regions of $[0, 1]^2$, namely I: entire 33×33 -grid, II: interior 31×31 -grid, III: interior 27×27 -grid.

6 Concluding Remarks

We introduced a novel technique to derive smooth approximations for solutions of systems of differential equations, which is based on sparse SDP relaxations and the maximum entropy

M	region	$\bar{\epsilon}_u(M)$	$\epsilon_u^{\max}(M)$
3	I	0.0177	0.3476
4	I	0.0232	0.9817
4	II	0.0071	0.2921
4	III	-0.0057	0.0352
5	I	0.0232	1.100
5	II	0.0072	0.0211
5	III	-0.0051	0.0126

Table 6: Errors for nonlinear PDE (13) with boundary conditions (14)

M	region	$\bar{\epsilon}_u(M)$	$\epsilon_u^{\max}(M)$	$\bar{\epsilon}_v(M)$	$\epsilon_v^{\max}(M)$
2	I	0.1374	1.3476	0.0673	0.5398
3	I	0.1392	1.8304	0.0675	0.5216
3	II	0.0958	1.3160	0.0471	0.4104
3	III	0.0246	0.6445	0.0127	0.2383
4	I	0.1846	5.1831	0.0912	1.4288
4	II	0.0604	2.2109	0.0283	0.7128
4	III	-0.0467	0.4065	-0.0258	0.1439

Table 7: Errors for nonlinear PDE (13) with boundary conditions (15)

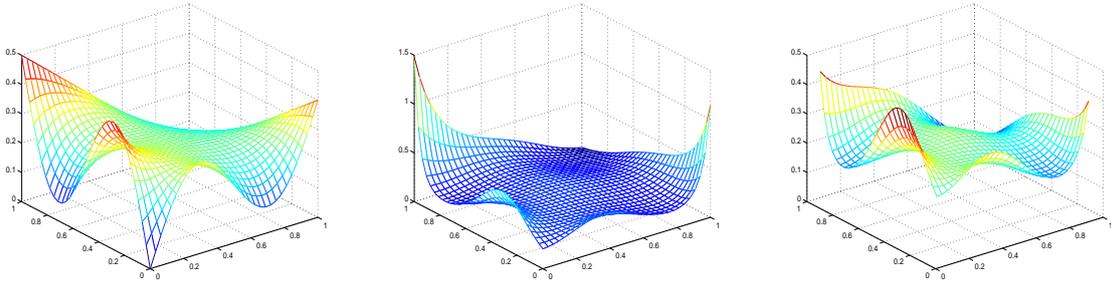


Figure 3: $(u_{i,j})_{i,j}$ (left), u_4^* on entire (center) and interior (right) domain for nonlinear PDE (13) with boundary conditions (14)

estimation method. As demonstrated on some examples of nonlinear ordinary and partial differential equations, this technique is promising to obtain accurate pointwise approximations of a solution of a differential equation on segments of its domain. It would be interesting to characterize regions of the domain of nonlinear differential equations where accurate pointwise approximations can be guaranteed. Another question is whether a different, less restrictive parametrization than (6) allows better pointwise approximations on larger segments of the domain.

In order to validate these techniques in the present context of PDEs, a comparison with state-of-the-art numerical methods for solving nonlinear PDEs remains to be done. In particular, the maximum entropy technique should be compared with standard and Spline interpolation methods which both provide differentiable approximations that coincide with the discrete solution at each grid point. But, unlike our method, in polynomial interpolation the *degree* of the polynomial is directly related to the number of grid points. Also, Cubic Splines are twice differentiable at the grid points, whereas our approximation is smooth. In contrast, and instead of searching for a smooth solution that matches the unknown u at the grid points, one searches for a smooth solution that matches finitely many *moments* of the associated measure $d\mu = u dx$. And so, an interesting feature is to obtain a smooth approximation from a limited number of *moments* and not from the discrete solution explicitly (still, before using moments, a sufficiently fine discretization is necessary to ensure $m^\Delta \approx m$). This method is an attempt to deal with the *curse of dimensionality* in the numerical analysis of PDE. A detailed comparison is however out of the scope of this paper, whose main objective was to pave the way for the development of SDP techniques to solve optimal control design problems for dynamical systems described by polynomial ODEs and PDEs, in the spirit of [4].

Acknowledgements

The research of M. Mevissen was supported by the Doctoral Scholarship of the German Academic Exchange Service. The research of D. Henrion was partly supported by project No. 103/10/0628 of the Grant Agency of the Czech Republic.

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