Constrained Derivative-Free Optimization on Thin Domains *

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Abstract

Many derivative-free methods for constrained problems are not efficient for minimizing functions on "thin" domains. Other algorithms, like those based on Augmented Lagrangians, deal with thin constraints using penalty-like strategies. When the constraints are computationally inexpensive but highly nonlinear, these methods spend many potentially expensive objective function evaluations motivated by the difficulties of improving feasibility. An algorithm that handles efficiently this case is proposed in this paper. The main iteration is splitted into two steps: restoration and minimization. In the restoration step the aim is to decrease infeasibility without evaluating the objective function. In the minimization step the objective function f is minimized on a relaxed feasible set. A global minimization result will be proved and computational experiments showing the advantages of this approach will be presented.

Key words: Derivative-Free Optimization, Disconnected Domains, Global Convergence, Numerical Experiments, Thin Domains.

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1 Introduction

In many practical problems one needs to minimize functions whose derivatives, for different reasons, are not available. The recent book by Conn, Scheinberg and Vicente [13] surveys the most relevant existing approaches for the unconstrained case and predicts that much research should be expected with regards to constrained problems in forthcoming years. Unconstrained techniques based on local explorations, line searches or quadratic models can be suitably adapted to box-constrained and linearly constrained derivative-free optimization [11, 14, 18, 19, 20, 31]. Mesh adaptive direct search methods [3, 5] are very effective for practical problems in which a "robust" feasible set may be efficiently explored by means of local samples that do not involve function evaluations at infeasible points. Problems with more general constraints were addressed by means of Augmented Lagrangian approaches in [15, 29] and [21, 22]. In [21] the Augmented Lagrangian method is based on the Lancelot approach [10], whereas in [15] and [22] the authors use the Algencan framework [1]. (See `www.ime.unicamp.br/~egbirgin/tango`.) In [15] two types of constraints are considered: the "difficult" ones are included in the augmented formulation of the Lagrangian, whereas "easy" constraints remain in the subproblems that are solved at each outer iteration. In this way, subproblems may be effectively solved by specific algorithms or by algorithms based in the MADS [3] approach. Easy constraints may be sometimes identified with the "non-relaxable" constraints considered in [4].

The Augmented Lagrangian approach imposes the evaluation of the objective function and the (difficult) constraints at the same (perhaps infeasible) points. This is not convenient when the objective function is very expensive to compute and the current point is infeasible. In this case we would like to restore feasibility without spending objective function evaluations, a resource that is not available in Augmented Lagrangian methods.

On the other hand, methods that maintain feasibility of all the iterates, as MADS-like and barrier methods, cannot work well in the presence of nonlinear equality constraints, or nonlinear very thin domains.

This state of facts motivated us to revisit a traditional approach for derivative-free nonlinear programming. In 1969, Paviani and Himmelblau [28] adapted the simplex Nelder-Mead method [27] for constrained optimization. Their iterative method employs a decreasing tolerance for infeasibility that depends on the simplex size. Whenever a trial point violates that tolerance, it is replaced by a restored point whose feasibility violation can be admitted. Clearly, this procedure produces severe simplex deformations which impair its chances of practical convergence. However, the idea of using

decreasing infeasibility tolerances is quite valuable and has been employed in several modern methods for constrained (not necessarily derivative-free) optimization [7, 9, 16, 23, 24].

We will say that the feasible domain of an optimization problem is "thin" if at least one of the following two properties hold:

1. For "many" feasible points x, and for all ball centered in x, the volume of the intersection of this ball with the feasible set is very small, compared with the diameter of that intersection.

2. The domain is disconnected.

Observe that the second property is, in some sense, a limit case of the first one, since a disconnected domain may be connected by means of a finite number of segments and segments are obviously thin.

Except in pathological cases, a single equality constraint is enough to define a thin domain.

In general, we will focus on problems in which:

1. The evaluation of the objective function is very costly, but the constraints are easy to evaluate.

2. Derivatives of the objective function are not available. Gradients of the constraints may be available or not.

3. The problem contains highly nonlinear constraints, whose fulfillment could be difficult to achieve.

At each iteration of the algorithm introduced in this paper, we define a relaxed "thick" domain on which we (approximately) minimize the objective function using some algorithm that, presumably, handles efficiently thick cases. We use a restoration procedure that does not involve the objective function for initializing the subproblem resolution. The infeasibility tolerance for the relaxed domain tends to zero as far as iterations advance. The combination of objective-function-free restorations and derivative-free relaxed minimizations produces a sequence that converges to the solution of the original problem, under reasonable algorithmic conditions.

The main algorithm will be described in Section 2, where we give a global convergence result. In Section 3 we describe a computer implementation. In Section 4 we show numerical experiments. Section 5 is devoted to conclusions of the present work.

Notation

We denote $\mathbb{N} = \{0, 1, 2, \ldots\}$.

We define $\mathbb{R}_+ = \{t \in \mathbb{R} \mid t \geq 0\}$ and $\mathbb{R}_{++} = \{t \in \mathbb{R} \mid t > 0\}$.

$\mathcal{B}(x, \Delta)$ denotes the closed ball with center x and radius Δ, with respect to a given norm $\|\cdot\|$.

2 Algorithms

The problem under consideration in this paper is:

$$\text{Minimize } f(x) \text{ subject to } g(x) \leq 0 \text{ and } x \in \Omega, \tag{1}$$

where $f : \mathbb{R}^n \to \mathbb{R}$, $g : \mathbb{R}^n \to \mathbb{R}^p$ and $\Omega \subseteq \mathbb{R}^n$ is closed. Equality constraints of the form $h(x) = 0$ are supposed to be replaced in (1) with the two obvious inequalities $h(x) \leq 0, -h(x) \leq 0$. The set Ω represents non-relaxable constraints in the sense of [4].

A high-level description of the main algorithm is given below.

Algorithm 1.1

Let $x^0 \in \Omega$ be an initial approximation. Let $w^1 \in \mathbb{R}^p_+$. Set $k \leftarrow 1$.

Step 1 (Restoration)

Compute $y^k \in \mathbb{R}^n$ such that $g(y^k) \leq w^k$ and $x \in \Omega$.

Step 2 (Minimization)

Using Algorithm 1.2 below, compute an "approximate solution" x^k of the following subproblem:

$$\text{Minimize } f(x) \text{ subject to } g(x) \leq w^k \text{ and } x \in \Omega. \tag{2}$$

(Points that satisfy $g(x) \leq w^k$ and belong to Ω will be said to be "w^k-feasible" from now on.)

Step 3 (Updating)

Choose $w^{k+1} \in \mathbb{R}^p_+$, set $k \leftarrow k + 1$ and go to Step 1.

Note that the restoration step plays no role in the formal definition of the algorithm. The restored point y^k will be used, in practice, as initial approximation for solving the subproblem (2).

Algorithm 1.2 describes the way in which x^k is computed at Step 2 of Algorithm 1.1 and, in fact, defines what we mean by "approximate solution"

of the subproblem (2).

Algorithm 1.2 (Minimization Step at Algorithm 1.1)

Assume that $\beta > 1$, $\Delta > 0$, $\eta_k > 0$, m_k is a given positive integer and y^k comes from the restoration Step 1 of Algorithm 1.1. Define $z^0 = y^k$ and set $\ell \leftarrow 0$.

Step 1 (Improvement step)

Find $z \in \Omega$ such that $g(z) \leq w^k$ and $f(z) \leq f(z^\ell)$ (Note that $z = z^\ell$ is an admissible choice.) Set $z^{\ell+1} = z$ and $\ell \leftarrow \ell + 1$.

Step 2 (Poll step)
Set $V_k \leftarrow \emptyset$, $j \leftarrow 1$ and choose $\eta_{k,\ell} \in [\eta_k, \beta\eta_k]$.

Step 2.1
Compute a "pseudo-random" direction $v \in \mathcal{B}(0, \Delta)$.

Step 2.2
If $z^\ell + v$ is w^k-feasible, define $\varphi_k(v) = v$ and go to Step 2.3. Else, try to find, by means of restoration, a new direction $\varphi_k(v)$ such that $z^\ell + \varphi_k(v)$ is w^k-feasible. If this procedure is successful, go to Step 2.3. Else, go to Step 2.4.

Step 2.3
If

$$f(z^\ell + \varphi_k(v)) < f(z^\ell) - \eta_{k,\ell} \ ,$$

define $z^{\ell+1} = z^\ell + \varphi_k(v)$, set $\ell \leftarrow \ell + 1$ and go to Step 1. Else, go to Step 2.4.

Step 2.4
Set $V_k \leftarrow V_k \cup \{v\}$.
If $j = m_k$, set $x^k = z^\ell$ and return to Step 3 of Algorithm 1.1. Else, set $j \leftarrow j + 1$ and go to Step 2.1.

At Step 1 of Algorithm 1.2 one tries to improve the objective function value in the region defined by $g(x) \leq w^k, x \in \Omega$. The idea will be to use a well-established method for thick-constrained derivative-free optimization for this purpose, trying to assure that x^k is w^k-feasible. This step is not

essential for proving global convergence, which is based on the procedure adopted at Step 2. At this step one chooses an arbitrary "pseudo-random" point on the ball with radius Δ centered on the current w^k-feasible point and we "project" this point on the w^k-feasible region. If, after m_k consecutive trials, the objective function fails to decrease enough or restoration cannot be completed, the algorithm returns the last iterate computed by Algorithm 1.2. The following assumptions guarantee that Algorithm 1.1, with Algorithm 1.2 at the minimization step, finds global minimizers within a ball of radius Δ. If Ω is bounded and Δ is large enough, this means that global minimizers of the original problems are found up to any arbitrary precision.

Assumption P1

The functions f and g are continuous.

Assumption P2

For all $w \geq 0$ the function f is bounded below on set defined by $x \in \Omega$ and $g(x) \leq w$.

Under Assumptions P1 and P2, it is easy to see that Algorithm 1.2 returns in finite time. Otherwise, we would have an infinite sequence such that $f(z^{\ell+1}) < f(z^\ell) - \eta_{k,\ell} \leq f(z^\ell) - \eta_k$ for all ℓ and, thus, $\lim_{\ell\to\infty} f(z^\ell) = -\infty$. Moreover, Assumption P2 is not restrictive, since it may be guaranteed by the addition of bound constraints on the original problem.

Assumption A1

The sequences $\{\|w^k\|\}$ and $\{\eta_k\}$ tend to zero.

Assumption A2

If $\{x^k\}_{k\in K}$ is a convergent subsequence generated by Algorithm 1.1, the set V, defined by

$$V = \bigcup_{k\in K} V_k,$$

is dense in $\mathcal{B}(0, \Delta)$.

Assumption A2 resembles the density requirements of the MADS framework but makes no use of dense directions in the unitary sphere lying in integer lattices. Our approach is closely connected to the simple framework described in [33], where the use of sufficient decrease and dense directions

in the unitary sphere avoided the necessity of integer lattices.

Assumption A3

If $\{x^k\}_{k\in K}$ is a convergent subsequence generated by Algorithm 1.1, $g(z) \leq 0, z \in \Omega$, $v^k \in V_k$ for all $k \in K$, and $\lim_{k\in K} x^k + v^k = z$, then, for all $k \in K$ large enough, the restoration procedure that computes $\varphi_k(v^k)$, at Step 2.2 of Algorithm 1.2, is successful.

Assumption A3 deserves some comments. In the definition of Algorithm 1.1 we stated that $w^k \geq 0$ for all k. Thus, we could choose, in principle, $w^k = 0$ for all k and, as we will see below, convergence can be proved even in this case. The reason why, in practice, we will choose $w^k > 0$ for all k is that, when $w^k = 0$, Assumption A3 very unlikely takes place. In fact, Assumption A3 says that, for k large enough, it is possible to restore with respect to the w^k-feasible region. In the case $w^k = 0$ this involves exact restoration with respect to all the constraints. If the constraints are nonlinear and thin, such restoration is generally impossible in finite time. The plausibility of Assumption A3 is, therefore, associated with the prescription that $w^k > 0$, at least when the feasible set is thin.

Assumption A4

If $\{x^k\}$, $\{v^k\}$, K, and z are as in Assumption A3, then

$$\lim_{k\in K} x^k + \varphi_k(v^k) = z.$$

Assumption A4 says that the operator φ_k resembles an orthogonal projector. In fact, if the set $\{x \in \Omega \mid g(x) \leq w^k\}$ was convex and $z^\ell + \varphi_k(v)$ was the projection of $z^\ell + v$ on this set, then the distance between $z^\ell + \varphi_k(v)$ and z would be not bigger than the distance between $z^\ell + v$ and z, for all feasible z. This would be enough to guarantee the fulfillment of Assumption A4. This observation suggests that a reasonable way to compute $\varphi_k(v)$ at Step 2.2 of Algorithm 1.2, consists of minimizing the distance between $z^\ell + v$ and the feasible set. When k is large and $z^\ell + v$ is close to the feasible set, it is reasonable to assume that a suitable algorithm not employing functional evaluations will be able to find a projection-like restored point that approximates $z^\ell + v$ to the feasible region, as required by Assumption A3.

Theorem 2.1. *Assume that $\{x^k\}$ is generated by Algorithm 1.1, Assumptions P1–P2 and A1–A4 hold, and x^* is a limit point of the sequence $\{x^k\}$.*

Then, x^* is a global solution of the problem

$$\textit{Minimize } f(x) \;\; \textit{subject to } \;\; g(x) \leq 0, \; x \in \Omega \; \textit{and } \; \|x - x^*\| \leq \Delta.$$

Proof. By the hypothesis, $g(x^k) \leq w^k$ and $x^k \in \Omega$ for all k. Then, by Assumptions P1 and A1, we have that $g(x^*) \leq 0$ and $x^* \in \Omega$.

Assume now that $\lim_{k \in K} x^k = x^*$. Let $z \in \Omega$ be such that

$$\|z - x^*\| \leq \Delta$$

and $g(z) \leq 0$. Since $z - x^* \in \mathcal{B}(0, \Delta)$, by Assumption A2 and the finiteness of V_k, there exists an infinite set of indices $K_1 \subseteq K$ and a sequence $\{v^k\}_{k \in K_1}$ such that $\lim_{k \in K_1} v^k = z - x^*$ and $v^k \in V_k$ for all $k \in K_1$. Thus, $\lim_{k \in K_1} x^k + v^k = z$. By Assumption A3, $\varphi_k(v^k)$ is well defined if k is large enough. By Assumption A4, this implies that $\lim_{k \in K_1} x^k + \varphi_k(v^k) = z$.

Then, by the return criterion of Algorithm 1.2, we have that, for $k \in K_1$ large enough,

$$f(x^k + \varphi_k(v^k)) \geq f(x^k) - \beta \eta_k.$$

Taking limits, by the continuity of f we have that $f(z) \geq f(x^*)$. □

Remarks

Since the famous anonymous paper [2] we know that one should be cautious about the interpretation of convergence results that use "density arguments". These results could be insufficient to explain efficiency and robustness of the methods to which they are applied. Moreover, the rigorous implementations of algorithms that guaranteedly satisfy density requirements could be unacceptably expensive, since full generation of dense sets demands a computational work that grows exponentially with the number of variables. However, in the global optimization framework, if one does not use specific information about the problem, only dense-set arguments can guarantee theoretical convergence to global optimizers. For similar reasons, dense-set arguments became popular for analyzing convergence of constrained derivative-free methods in the last few years. In general, density arguments have been used for proving convergence to different types of stationary points in this context [4, 5, 13].

In this section we proved that the Algorithm 1.1 obtains local minimizers within a fixed neighborhood of arbitrary radius $\Delta > 0$. If Δ is large enough and the feasible set is bounded this means that the algorithm finds global optimizers of the original problem. In spite of the drawbacks pointed out

above, the proof of Theorem 2.1, as many other density-based proofs, sheds some light on the characteristics that a practical algorithm should exhibit in order to be reasonably efficient.

Assume that x^* is a limit point of a sequence generated by Algorithm 1.1 and that z is a feasible point such that $\|z - x^*\| \leq \Delta$. The proof of Theorem 2.1 shows that, in order to obtain the desired property $f(z) \geq f(x^*)$ it is necessary to guarantee that, for k large enough, w^k-feasible points arbitrarily close to z are tested by the algorithm used to solve the subproblems. This property is guaranteed by the assumptions of the theorem, but, in practical terms, we need to satisfy it spending a moderate amount of computer work. This practical requirement prescribes that, at least for k large enough ($\|w^k\|$ small enough), $f(x^k)$ should be smaller than $f(x)$ for all x in a "not very small" set of w^k-feasible points in the ball $\mathcal{B}(x^k, \Delta)$. As a consequence of being "not very small", the probability that points in this set approximate any arbitrary feasible point z such that $\|z - x^*\| \leq \Delta$, may be significant as k grows (although, obviously, this probability decreases dramatically with n). Now, when $\|w^k\|$ is small, the probability of generating feasible points using, say, random generation or grids, may be very small. However, one of the assumptions of our problem is that constraints are cheap and only the objective function is expensive. Therefore, given possibly infeasible (random or grid) generated points, cheap restoration procedures may be used to generate close feasible ones.

Algorithm 1.2 may be implemented without the improvement step (equivalently, taking $z = z^\ell$ at Step 1). However, we wish to take advantage of the fact that several existing algorithms are efficient for solving (2) if $\|w^k\|$ is not excessively small. In our implementation, we will use DFO [11, 12] for finding z at the first step of Algorithm 1.2.

3 Implementation

Algorithm 1.1 has been implemented using Algorithm 1.2 at Step 2. At Step 1 of Algorithm 1.1 we consider the auxiliary problem

$$\text{Minimize } \|y - x^k\|_2^2 \text{ subject to } g(y) \leq \tau w^k \text{ and } y \in \Omega, \tag{3}$$

where $\tau \in [0, 1]$ is a given algorithmic parameter that controls the restoration effort. The point y^k, defined at Step 1 of Algorithm 1.1, is an approximate solution of (3). For solving this subproblem we use Algencan [1] with its default parameters, if constraint derivatives are available, and the standard coordinate search algorithm when derivatives of g are not available. In both

cases, we assume that the non-relaxable constraints define a box. If one fails to find an w^k-feasible point in the process of solving (3), we continue the execution of Algorithm 1.1 at Step 2 taking the (perhaps infeasible) output of (3) as initial approximation. Since, as mentioned in Section 2, the restored point y^k plays no role in the formal definition of the algorithm, this does not affect the convergence proof.

At Step 2 of Algorithm 1.2, we compute the direction v as a pseudo-random vector with uniform distribution in $\mathcal{B}(0, \Delta)$. For this purpose we use the method of Muller [26] to generate a pseudo-random vector $v' \in \mathbb{R}^n$ uniformly distributed in the unitary hypersphere. Then, we choose a pseudo-random number $\rho \in [0, 1]$ by means of Schrage's algorithm [32]. The vector $v = (\rho^{1/n}\Delta)v'$ turns out to be a pseudo-random vector uniformly distributed in the Euclidean ball $\mathcal{B}(0, \Delta)$ [6].

Similarly to (3), we compute $\varphi_k(v)$ as an approximate solution $\tilde{v}$ of

$$\text{Minimize } \|\tilde{v} - v\|_2^2 \text{ subject to } g(z^\ell + \tilde{v}) \leq w^k \text{ and } z^\ell + \tilde{v} \in \Omega. \quad (4)$$

In this way, $z^\ell + \varphi_k(v)$ has the flavor of a projection of $z^\ell + v$ on the feasible set, as required by the theoretical Assumption A4.

For solving (4) we proceed as in the subproblem (3). The case in which restoration is not successful is covered by Step 2.2 of Algorithm 1.2.

At Step 1 of Algorithm 1.2 (improvement step) we use DFO [11], a derivative-free trust region algorithm for unconstrained problems which is also able to handle general smooth constraints. When dealing with constraints, DFO acts as an heuristic method that computes only feasible points and, at each iteration, minimizes a quadratic model of the objective function subject to the problem's constraints and a suitable trust region [12]. For solving the smooth constrained trust region subproblems required in DFO we use Algencan. Note that DFO can be applied to the original problem (1). In fact, we will apply DFO directly to (1) for numerical comparisons in Section 4.

Tolerances, stopping criteria and other implementation details are given below.

1. At Algencan executions for solving (3) and (4) we use x^k and v as initial points, respectively. We employ the default parameters of Algencan, using 10^{-8} as stopping criteria both for feasibility and optimality.

2. The rule for updating the tolerances w^k is as follows. Initially, we define
$$w_i^1 = \max\{10, \|g(x^0)\|_\infty\}, \quad \forall i = 1, \ldots, p. \quad (5)$$

At the end of each iteration of Algorithm 1.1 we force the point x^k, returned from the minimization step, to be w^{k+1}-infeasible, taking:

$$w_i^{k+1} = \max\{10^{-8}, \theta \min\{w_i^k, \|g(x^k)\|_\infty\}\}, \quad \forall i = 1, \ldots, p, \quad (6)$$

where $\theta \in (0, 1)$. In the experiments reported in this paper we used $\theta = 0.1$.

3. The objective function used in the improvement step by DFO has a fixed penalization of the infeasibility:

$$\bar{f}(x) = f(x) + \rho \|g(x)_+\|_2^2,$$

where $g(x)_+ = \max\{0, g(x)\}$ (in vector form) and

$$\rho = \max\{1, |f(x^0)|\} / \max\{1, \|g(x^0)\|_\infty\} \quad (7)$$

is the penalty parameter.

Note that the parameter ρ is fixed and that the problem of minimizing $\bar{f}(x)$ subject to $g(x) \leq 0$ and $x \in \Omega$ is equivalent to the original problem (1), so, there is no loss of generality when we consider $\bar{f}(x)$ instead of the original $f(x)$ in the algorithm. Since we assume that the constraints are cheap and ρ is fixed, there is no loss of stability and no significative increase of computer time can be attributed to this replacement.

4. We employ the default parameters of DFO in the improvement step. The following stopping criteria were modified: trust region radius smaller than $\min\{10^{-1}, \max\{10^{-3}, \|w^k\|_\infty^2\}\}$, maximum of $1000n$ function evaluations and maximum of 1000 iterations. In the constrained trust region subproblems solved by Algencan in the context of DFO, we use 10^{-8} as stopping criteria for both optimality and feasibility.

5. The objective function used in the poll step is the extreme barrier function [3] with fixed penalization of the infeasibility:

$$\tilde{f}(x) = \begin{cases} f(x) + \rho \|g(x)_+\|_2^2, & \text{if } x \text{ is } w^k\text{-feasible} \\ 10^{99}, & \text{otherwise,} \end{cases} \quad (8)$$

where the parameter ρ is defined by equation (7).

6. The sufficient decrease parameter η_k is defined as $\eta_k = 10^{-8}/k$, for $k = 1, 2, \ldots$ The parameter β is set to 10^{16}. For each $\ell = 1, 2, \ldots$, in Algorithm 1.2 we use

$$\eta_{k,\ell} = \max\{\eta_k, \min\{\|g(z^\ell)\|_\infty, \eta'_k, \beta\eta_k\}\}, \tag{9}$$

where η'_k is defined as follows:

$$\eta'_k = \begin{cases} 0.01 \max\{1, |f(x^0)|\}, & \text{if } k = 1 \\ \min\{0.5\eta'_{k-1}, \|w^k\|_\infty\}, & \text{if } k > 1. \end{cases}$$

Equation (9) guarantees that $\eta_{k,\ell} \in [\eta_k, \beta\eta_k]$, as required by Algorithm 1.2, and the formula of η_k guarantees that $\eta_k \to 0$. So, we ask for a substantial decrease in the poll step, unless we already have a feasible point. The idea is that we are leaving to the improvement step (DFO) the main work at the first iterations and only when x^k becomes almost feasible, the poll step really acts.

7. We choose $m_k = 2n$ for all k. In (3) and (4) we use $\tau = 0.1$. We also set $\Delta = 1$.

8. The algorithm declares success when, at the end of the minimization step, it finds that $g(x^k) \leq 10^{-8}$. It declares failure when $\|w^k\|$ becomes smaller than 10^{-8} and the current point x^k is not w^k-feasible or when the algorithm reaches the maximum of 10^3 iterations or the maximum of 10^6 functional evaluations.

4 Numerical Experiments

We compared our algorithm against a C$_{++}$ implementation of an Augmented Lagrangian derivative-free algorithm [22], called HOPSPACK [30], and a Fortran implementation of DFO. For now on, Algorithm 1.1, with the implementation described in the previous section, will be called *Skinny*.

We employed 47 problems from [17] in our tests. All the problems in this subset exhibit thin domains, since they include at least one equality constraint. The derivatives of the constraints were used by DFO and by Algencan in the restoration problems (3) and (4). *Skinny* was implemented in Fortran 90 and DFO in Fortran 77. Both were compiled with `gfortran-4.2` and ran on a computer with 8GB of RAM, two Intel Core i7 2.67GHz processors and 64bit Linux (Ubuntu) operational system. The problems considered in this study are reported in Table 1, using their numbers in [17]. In

this table Var means number of variables, Ineq is the number of inequality constraints and Eq is the number of equality constraints.

Prob.	Var.	Ineq.	Eq.	Prob.	Var.	Ineq.	Eq.	Prob.	Var.	Ineq.	Eq.
6	2	0	1	49	5	0	2	74	4	2	3
7	2	0	1	50	5	0	3	75	4	2	3
8	2	0	2	51	5	0	3	77	5	0	2
9	2	0	1	52	5	0	3	78	5	0	3
14	2	1	1	53	5	0	3	79	5	0	3
26	3	0	1	54	6	0	1	80	5	0	3
27	3	0	1	55	6	0	6	81	5	0	3
28	3	0	1	56	7	0	4	87	6	0	4
32	3	1	1	60	3	0	1	99	7	0	2
39	4	0	2	61	3	0	2	107	9	0	6
40	4	0	3	62	3	0	1	109	9	4	6
41	4	0	1	63	3	0	2	111	10	0	3
42	4	0	2	68	4	0	2	112	10	0	3
46	5	0	2	69	4	0	2	114	10	8	3
47	5	0	3	71	4	1	1	119	16	0	8
48	5	0	2	73	4	2	1				

Table 1: Description of the test problems.

For algorithmic comparisons we used data and performance profiles as described in [25]. We will consider that an algorithm has successfully converged if the obtained solution $\bar{x}$ is feasible and:

$$\frac{|f(\bar{x}) - f_{\mathrm{L}}|}{\max\{1, |f(\bar{x})|, |f_{\mathrm{L}}|\}} \leq 10^{-1}, \tag{10}$$

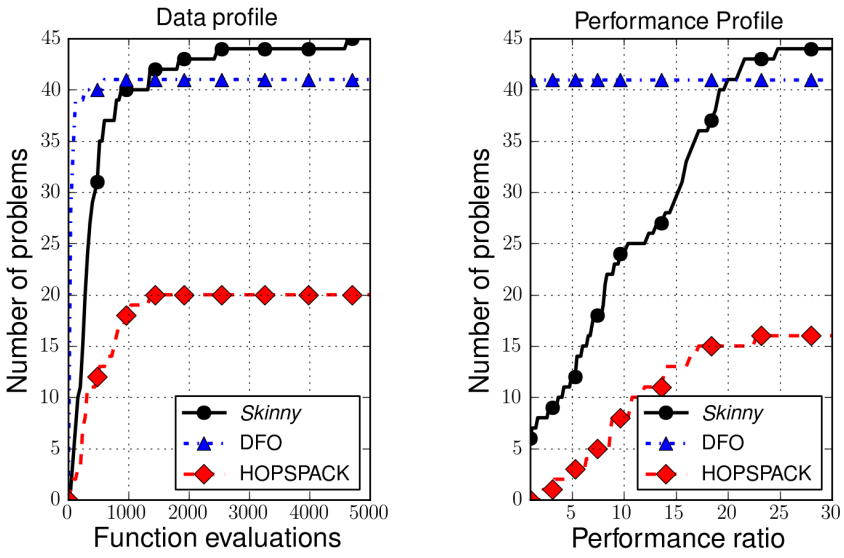
where f_{L} is the best value of f among the feasible solutions found by the compared algorithms. The number of function evaluations was used as performance measure.

For the numerical comparisons, we required a feasibility tolerance of 10^{-8} in the three algorithms. In Algencan we employed the default algorithmic parameters. Table 2 shows the numerical results, where the first column is the problem's number and, for each algorithm, f is the functional value and #FE is the number of objective function evaluations. A maximum of 20 minutes of CPU time was allowed for each problem and the the symbol '*' indicates that a feasible point could not be obtained.

Table 2 shows that *Skinny* was always able to find a feasible point, while DFO failed to find feasible points in 6 problems and HOPSPACK failed in 20 problems. The comparisons between *Skinny* and HOPSPACK show the

Prob.	*Skinny* f	#FE	HOPSPACK f	#FE	DFO f	#FE
6	8.83040E-08	97	4.8400E+00*	151	2.20090E-23	14
7	-1.73210E+00	150	6.93147E-01	325	-1.73210E+00	10
8	-1.00000E+00	56	-1.0000E+00*	187	-1.00000E+00	3
9	-5.00000E-01	109	-5.00000E-01	26	-5.00000E-01	12
14	1.39350E+00	142	1.39411E+00	202	1.39350E+00	9
26	2.11600E+01	33	2.11600E+01	585	1.29420E-06	40
27	4.00000E+00	269	4.00056E+00	1358	4.00000E+00	33
28	3.68920E-27	43	7.70336E-08	264	2.30390E-18	25
32	1.00000E+00	209	1.00000E+00	51	1.00000E+00	11
39	-1.00000E+00	302	-1.00000E+00	830	-1.00000E+00	23
40	-2.50000E-01	215	-2.5056E-01*	897	-2.50000E-01	14
41	1.92590E+00	348	1.92593E+00	292	1.92590E+00	34
42	1.38580E+01	254	1.40000E+01	779	1.38580E+01	14
46	2.10900E-02	501	3.33763E+00	777	2.98290E-07	77
47	1.45480E-08	302	1.24954E+01	901	1.87140E-06	50
48	1.49690E-16	76	1.11743E-06	497	1.27110E-18	29
49	3.73880E-05	261	1.42943E-04	1002	2.78010E-05	72
50	7.70300E-06	246	5.29367E-07	290	2.13690E-07	46
51	8.46710E-17	88	1.25372E-06	142	1.10250E-18	16
52	5.32670E+00	337	5.3267E+00*	311	5.32660E+00	20
53	4.09300E+00	295	4.09302E+00	216	4.09300E+00	18
54	-1.55810E-01	335	-	-	-1.53990E-01	20
55	6.33330E+00	223	-	-	6.66670E+00	9
56	-1.00000E+00	93	-1.00000E+00	2075	-3.45600E+00	45
60	3.25700E-02	236	5.47089E-02	465	3.25710E-02	29
61	-1.43650E+02	196	-1.43000E+02	621	0.0000E+00*	1
62	-2.56980E+04	33	-2.62716E+04	233	-2.62730E+04	32
63	9.61720E+02	159	9.62606E+02	317	9.61720E+02	10
68	-9.20410E-01	439	-8.4354E-01*	1316	-9.20420E-01	106
69	-9.56710E+02	581	-9.5665E+02*	2471	-9.51070E+02	73
71	1.70140E+01	398	1.7031E+01*	1939	1.6000E+01*	1
73	2.98940E+01	305	3.01595E+01	223	2.98940E+01	16
74	5.12650E+03	279	5.1447E+03*	46145	0.0000E+00*	1
75	5.17440E+03	2453	5.2331E+03*	22678	0.0000E+00*	1
77	2.41510E-01	598	4.6807E+00*	1904	2.41510E-01	85
78	-2.91970E+00	368	-2.8917E+00*	869	-2.91970E+00	27
79	7.87770E-02	495	2.4186E-01*	1054	7.87770E-02	40
80	5.39500E-02	458	1.0000E+00*	557	5.39500E-02	23
81	5.39500E-02	481	9.9999E-01*	557	5.39500E-02	23
87	8.92760E+03	493	9.3254E+03*	16244	4.2090E+04*	1
99	-8.31080E+08	777	-7.4573E+08*	729	-8.31080E+08	82
107	5.05500E+03	858	5.0628E+03*	7232	5.05500E+03	23
109	5.36210E+03	775	5.5010E+03*	57551	0.0000E+00*	1
111	-4.77610E+01	4607	-	-	-4.77600E+01	561
112	-4.77610E+01	1815	-4.77608E+01	730	-4.77600E+01	85
114	-1.76880E+03	1359	-	-	-1.76880E+03	276
119	2.44900E+02	1331	2.44926E+02	944	2.44900E+02	90

Table 2: Comparison among *Skinny*, HOPSPACK and DFO in 47 problems having thin domains. The function values marked with '*' are infeasible solutions.



(a) (b)

Figure 1: Data (a) and performance (b) profiles for the comparison among *Skinny*, DFO and HOPSPACK.

advantages of separating the minimization from the feasibility process when the latter is computationally easier. The data profile in Figure 1(a) shows that *Skinny* converged in 45 problems while HOPSPACK converged only in 20. Moreover, using the same number of function evaluations, *Skinny* solved approximately two times the number of problems that HOPSPACK solved. The number of infeasible points found by HOPSPACK can be decreased if we strengthen its stopping criteria, at the cost of an enormous increase in the number of function evaluations.

The comparison of *Skinny* against DFO shows that the first is more robust (it solves more problems) whereas DFO is more efficient in the sense that, when both algorithms solve a problem, DFO spends less functional evaluations. Both features were expected since both the constraint-relaxing strategy and the Poll Step of *Skinny* aim to improve robustness, and may be unnecessarily conservative when the problems are easy.

4.1 The case $w^k = 0$

The good performance of stand-alone DFO and the fact that the convergence theory of *Skinny* does not depend on $w^k > 0$ raised up the question about the possible advantages of working with the original domains ($w^k = 0$) instead of w^k-feasible sets.

We compared this new version of *Skinny* against its standard version and against DFO, in the same set of 47 problems described in Table 1. For each algorithm in Table 3, Feas is the number of problems it has found a feasible solution, Conv is the number of problems it has converged, in the sense of the performance profiles, and Eff is the number of problems that it was the fastest. In the last three columns we show the number of problems in which each algorithm has spent up to 10^2, between 10^2 and 10^3 and more than 10^3 function evaluations, respectively. We can see that *Skinny* with $w^k = 0$ performs very similarly to DFO in terms of of function evaluations and also inherits the good convergence properties of the presented theory, converging in 46 problems.

	Feas.	Conv.	Eff.	Function evaluations		
				$[0, 10^2]$	$(10^2, 10^3]$	$(10^3, 10^4]$
DFO	41	41	34	38/41	3/41	0/41
Skinny $w^k = 0$	47	46	13	42/47	3/47	2/47
Skinny	47	45	1	8/47	34/47	5/47

Table 3: *Skinny* with $w^k = 0$ performed better than *Skinny* using w^k-feasible sets and had a behavior similar to DFO.

The naive conclusion is that it is better to use $w^k = 0$ instead of $w^k > 0$, but the real fact is that the domains of the test problems are not harder to work than their respective w^k-relaxation.

To show the advantages of working with $w^k > 0$, suppose now that the feasible domain of the problem is **thin** and also **disconnected**. As an example, we present the integer programming problem of minimizing $f(x) = x^2$ subject to $x \in \{1, 2, 3, 4, 5\}$. The integrality constraint can be written as the differentiable equality constraint $\prod_{i=1}^{5}(x - i) = 0$ and the global minimizer is $x^* = 1$. Suppose that the starting point is $x^0 = 10$.

Using $w^k = 0$, *Skinny* first finds $y^1 = 5$ as a feasible point in the restoration step. There is nothing to be done by DFO, since this point is a local minimizer and then, after the poll step, *Skinny* declares convergence to $\bar{x} = 5$. Now, using a sufficiently large w^k, all the disconnections in the domain disappear and the initial w^k-feasible set is an interval containing the

points $\{1, 2, 3, 4, 5\}$. DFO is able to converge to the global unconstrained minimizer $x^1 = 0$ and, in the steps that follow, the global solution of the problem is found. Figure 2 outlines the general idea of connection in disconnected domains when $w^k > 0$.

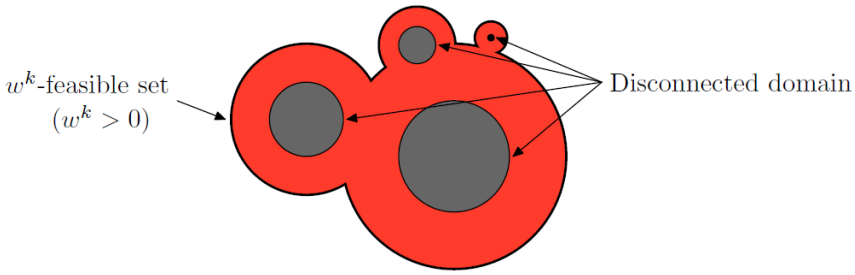


Figure 2: A sufficiently positive value for w^k connects disconnected domains.

Another advantage of working with $w^k > 0$ is when a direct search method is more indicated to a problem than DFO. In the same way as DFO cannot deal with disconnected domains, direct search methods are not able to find feasible points on thin domains. As a consequence, if $w^k = 0$, *Skinny* will rely solely on the poll step, which will cause a performance decrease.

5 Final Remarks

We presented a new algorithm for derivative-free constrained optimization which, under suitable assumptions, converges to local minimizers associated with a neighborhood of fixed size Δ. Convergence to global minimizers takes place if the feasible domain is bounded and Δ is large enough.

The new algorithm is based on successive minimizations on relaxed feasible sets. Convergence proofs follow even without feasibility relaxation, but, in this case, assumptions are harder to satisfy. We are especially interested in problems in which the main computational cost is associated with objective function evaluations, whereas the feasible set may exhibit high nonlinearity that could complicate the process of getting feasible points.

Handling thin feasible regions (and, in the limit, disconnected domains) may be particularly hard for algorithms based on direct search or Augmented Lagrangian approaches. Direct search methods have severe difficulties for preserving feasibility whereas penalty-like methods may spend many unnecessary functional evaluations motivated by the necessity of achieving feasibility.

We compared the new method against two well-established derivative-free algorithms: the first is based on Augmented Lagrangians [22, 30] and the second one is supported on trust-region ideas [11, 12]. In principle, these algorithms are able to handle thin feasible regions. Moreover, the Augmented Lagrangian method may be implemented in such a way that convergence to global minimizers holds [8]. The numerical results show that our algorithm spends less function evaluations than the Augmented Lagrangian method and almost always finds a feasible solution. Moreover, we showed the advantages of working with w^k-feasible sets ($w^k > 0$) in problems having disconnected thin domains. The new algorithm also showed to be more robust than the trust-region method DFO.

The flexibility of the new algorithm allows one to use different derivative-free methods both in the restoration phase as in the minimization phase.

The source code of the algorithm and the complete tables with the numerical results are available in `http://www.ime.unicamp.br/~ra079963/skinny`.

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