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A PRIMAL-DUAL ALGORITHM FOR NONLINEAR PROGRAMMING EXPLOITING NEGATIVE CURVATURE DIRECTIONS

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Abstract

In this paper we propose a primal-dual algorithm for the solution of inequality constrained optimization problems. The distinguishing feature of the proposed algorithm is that of exploiting as much as possible the local non-convexity of the problem to the aim of producing a sequence of points converging to second order stationary points. In the unconstrained case this task is accomplished by computing a suitable negative curvature direction of the objective function. In the constrained case it is possible to gain analogous information by exploiting the non-convexity of a particular exact merit function. The algorithm hinges on the idea of comparing, at every iteration, the relative effects of two directions and then selecting the more promising one. The first direction conveys first order information on the problem and can be used to define a sequence of points converging toward a KKT pair of the problem. Whereas, the second direction conveys information on the local non-convexity of the problem and can be used to drive the algorithm away from regions of non-convexity. We propose a proper selection rule for these two directions which, under suitable assumptions, is able to generate a sequence of points that is globally convergent to KKT pairs that satisfy the second order necessary optimality conditions, possibly with superlinear convergence rate.

AMS subject classifications: 90C30

Key words: Nonlinear programming, augmented Lagrangian function, primal-dual algorithm, second order necessary optimality conditions, negative curvature direction.

1. Introduction

We consider the smooth constrained optimization problem:

$$\begin{array}{ll} \min & f(x) \\ & g(x) \le 0, \end{array} \tag{1}$$

where $x \in \mathbb{R}^n$ and $f: \mathbb{R}^n \to \mathbb{R}$, $g: \mathbb{R}^n \to \mathbb{R}^m$ are three times continuously differentiable functions. However, we point out that computation of third-order derivatives is never required by the proposed algorithm.

A Karush-Kuhn-Tucker (KKT) pair for Problem (1) is a pair $(\bar{x}, \bar{\lambda}) \in \mathbb{R}^{n+m}$ such that

$$\nabla_x L(\bar{x}, \bar{\lambda}) = 0, \quad \bar{\lambda}' g(\bar{x}) = 0, \quad g(\bar{x}) \le 0, \quad \bar{\lambda} \ge 0, \tag{2}$$

where $L(x, \lambda) = f(x) + \lambda' g(x)$ is the Lagrangian function for Problem (1) and $\lambda \in \mathbb{R}^m$ is the KKT multiplier. The *strict complementarity* condition holds at $(\bar{x}, \bar{\lambda})$ if $\bar{\lambda}_j > 0$ for all j such that $g_j(\bar{x}) = 0$.

If the *linear independence constraints qualification* (LICQ) holds at $\bar{x}$, namely if the gradients $\nabla g_j(\bar{x})$ with $j: g_j(\bar{x}) = 0$ are linearly independent, then (2) are first order necessary optimality conditions for Problem (1). The second order necessary optimality conditions (SONC) are satisfied in a KKT pair $(\bar{x}, \bar{\lambda})$ if

$$y' \nabla_x^2 L(\bar{x}, \bar{\lambda}) y \ge 0, \quad \forall\, y: \ \nabla g_j(\bar{x})' y = 0 \quad \text{with } j: \ g_j(\bar{x}) = 0. \tag{3}$$

Standard algorithms for constrained minimization usually generate sequences converging to KKT pairs. In this paper we define a primal-dual algorithm model, suitable having the potential for large-scale problems, that generates a sequence $\{(x^k, \lambda^k)\}$ converging to KKT pairs satisfying also the second order necessary conditions for optimality. Of course, convergence to second order stationary points allows us to better select among the points candidate to be solutions of Problem (1).

Trust-region algorithms convergent to second order stationary points have been developed for equality constrained and box constrained problems [2, 4, 6, 11, 23, 26, 28]. In [5] an interior point primal-dual trust-region method for problems with general inequality constraints and linear equality constraints has been proposed. In [27] an infeasible interior point method based on a trust region strategy has been proposed that uses a log-barrier function for the slack variables. Line search algorithms have been proposed at the beginning for the linear inequality constrained case [16, 20], and then also for the more complex nonlinear inequality constrained Problem (1). In particular, in [24] the inequality constrained problem is reduced, by the introduction of slack variables, to an equality constrained one which is then dealt with by means of an exact penalty function. In [1], a negative curvature Armijo type linesearch approach is used in connection with a sequential penalty approach. In [14], a curvilinear search approach has been proposed in connection with an exact penalty function. More recently, in [21] an interior point method with a curvilinear search has been proposed which uses negative curvature directions in connection with an augmented Lagrangian function with the additional restriction on the infeasibility of the current iterate.

Of course, the definition of algorithms converging to second order points needs the use of second order information of the constrained problem that requires additional computational burden with respect to first order convergent algorithms.

This paper aims to combine the use of an exact augmented Lagrangian function, as described in [8], with the idea presented in [15] where an alternating strategy for the selection of the search direction is used. Indeed our algorithm scheme belongs to the class of linesearch methods and it is based on the unconstrained reformulation of the constrained problem by means of an exact augmented Lagrangian function.

The paper is organized as follows. In section 2 we describe the exact augmented Lagrangian function L_a employed in the paper. In particular we use the exact augmented Lagrangian function L_a studied in [9], where it is shown that the original constrained problem (1) is equivalent to the unconstrained minimization of L_a for sufficiently small values of a penalty parameter ϵ. We report the main exactness results that we need in the paper. Furthermore, we perform some second order analysis that plays a key role in the definition of the algorithm. Namely we show that points satisfying the SONC for problem (1) correspond to points satisfying some kind of second order optimality condition for the unconstrained problem (which is not twice continuously differentiable).
Section 3 is devoted to the computation of the search directions. In particular, we define two directions d_P, which is a positive curvature direction for the augmented Lagrangian L_a, and $\hat{d}_s$, which is a negative curvature direction and is able to enforce convergence toward KKT pairs that satisfy SONC.
Section 4 is dedicated to the definition of an adaptive linesearch technique (ALS) for the minimization of L_a for a fixed value of the penalty parameter ϵ.
In Section 5 we introduce the overall algorithm (SOLA) converging to points satisfying the SONC. Updating rules for ϵ that guarantee that it eventually stays fixed and that exactness properties are met, are defined here.

We conclude this section by introducing some notation.
We denote by $\mathcal{F} = \{x \in \mathbb{R}^n : g(x) \leq 0\}$ the feasible set of Problem (1). At a given point $x \in \mathbb{R}^n$, not necessarily feasible, we associate the index sets:

$$A_0(x) = \{j : \ g_j(x) = 0\}, \quad N_0(x) = \{j : \ g_j(x) < 0\}.$$

Given a vector $v \in \mathbb{R}^p$, we indicate by the uppercase V the diagonal matrix $V = \text{diag}_{1\leq i\leq p}\{v_i\}$.
Let $K \subseteq \{1, \dots, p\}$ be an index subset, we denote by v_K the subvector of v with components v_i such that $i \in K$.
Given two vectors $v, w \in \mathbb{R}^p$, the operation $\max\{v, w\}$ is intended component-wise, namely $\max\{v, w\}$ denotes the vector with components $\max\{v_i, w_i\}$.
We denote by $\|\cdot\|_p$ the ℓ_p norm, and when p is not specified we intend $p = 2$.

2. The augmented Lagrangian function

In the definition of the algorithm we make use of the following augmented Lagrangian function, introduced in [9]:

$$\begin{aligned} L_a(x, \lambda; \epsilon) \quad &= \quad f(x) + \lambda' \max\{g(x), -\epsilon p(x, \lambda)\lambda\} + \frac{\|\max\{g(x), -\epsilon p(x, \lambda)\lambda\}\|^2}{2\epsilon p(x, \lambda)} \\ &\qquad + \|\nabla g(x)'\nabla_x L(x, \lambda) + G(x)^2\lambda\|^2, \end{aligned}$$

where $\epsilon > 0$ is a penalty parameter and

$$p(x, \lambda) = \frac{a(x)}{1 + \|\lambda\|^2} \ , \tag{4}$$

with

$$a(x) = \alpha - \| \max\{g(x), 0\}\|_s^s \ ,$$

and the scalars α, s are such that $\alpha > 0$ and $s \geq 3$.

The function $L_a(x, \lambda; \epsilon)$ is defined on the set

$$\mathcal{P} = \{x \in \mathbb{R}^n : \ \alpha - \| \max\{g(x), 0\}\|_s^s > 0\},$$

which is an open perturbation of the feasible set $\mathcal{F}$, so that $\mathcal{F} \subset \mathcal{P}$.

We refer to [9] and [10] for a detailed discussion of the rationale behind the structure of the augmented Lagrangian $L_a(x, \lambda; \epsilon)$.

We point out that, given any point $x^0 \in \mathbb{R}^n$, it is easy to select values α and s that appear in the definition of $\mathcal{P}$, such that $x^0 \in \mathcal{P}$. Hence, given a point $(x^0, \lambda^0) \in \mathcal{P} \times \mathbb{R}^m$, we can introduce the level set of L_a defined by:

$$\Omega^0(\epsilon) = \{(x, \lambda) \in \mathcal{P} \times \mathbb{R}^m : L_a(x, \lambda; \epsilon) \leq L_a(x^0, \lambda^0; \epsilon)\}.$$

As we said before, our aim is to solve Problem (1) by an unconstrained minimization of L_a on $\mathcal{P} \times \mathbb{R}^m$. Therefore we are interested in the correspondence between stationary points of L_a belonging to $\Omega^0(\epsilon)$ and KKT pairs of Problem (1), as well as in the correspondence between local (global) minimizers of L_a belonging to $\Omega^0(\epsilon)$ and local (global) solutions of Problem (1).

The exactness properties of the function L_a employed in this paper can be stated under the following assumptions, which are discussed in details in [9]:

Assumption 1. *One of the two following conditions is satisfied:*

(a) $x^0 \in \mathcal{F}$ *and* $f(x)$ *is coercive on the closure* $\bar{\mathcal{P}}$ *of* $\mathcal{P}$ *, i.e. for any* $\{x^k\} \subseteq \mathcal{P}$ *with* $\|x^k\| \to \infty$ *we have* $f(x^k) \to \infty$*;*

(b) *the set* $\bar{\mathcal{P}}$ *is bounded and at every point* $x \in \mathcal{P}/\mathcal{F}$ *it results:*

$$\sum_{i: g_i(x) > 0} c_i(x) \nabla g_i(x) \neq 0,$$

where

$$c_i(x) = \left[1 + \frac{s}{2} \frac{\| \max\{g(x), 0\}\|^2 g_i(x)^{(s-2)}}{\alpha - \| \max\{g(x), 0\}\|_s^s}\right] g_i(x).$$

Assumption 2. *For every* $x \in \mathcal{F}$ *the gradients* $\nabla g_i(x)$ *with* $i \in A_0(x)$ *are linearly independent.*

Assumptions 1 and 2 are reasonable enough. In fact, Assumption 1(a) is equivalent to the compactness of the level sets of the objective function on the set $\mathcal{P}$ and it is similar to the one usually used in the unconstrained case. Assumption 1(b) is a weakening of the Mangasarian-Fromovitz constraint qualification condition and it ensures the existence of a feasible solution of the constrained problem. Assumptions 2 requires that the LICQ holds at every easible point and it guarantees the existence and uniqueness of the KKT multipliers.

In the sequel, we assume that Assumptions 1 and 2 hold.

The next proposition ensures that the essentially unconstrained problem

$$\min_{(x,\lambda)\in\Omega^0(\epsilon)} \quad L_a(x,\lambda;\epsilon)$$

is well defined, in the sense that a solution exists, and establishes the main exactness properties of the augmented Lagrangian function L_a.

Proposition 2.1 (See [9]) *Under Assumptions 1 and 2 it results:*

(a) for every $\epsilon > 0$ the level set $\Omega^0(\epsilon)$ is compact;

(b) a value $\bar\epsilon > 0$ exists such that for all $\epsilon \in (0, \bar\epsilon]$,

(i) *if $(\bar x, \bar\lambda) \in \Omega^0(\epsilon)$ is a stationary point of $L_a(x,\lambda;\epsilon)$, the pair $(\bar x, \bar\lambda)$ is a KKT pair for Problem (1).*

(ii) *if $(\bar x, \bar\lambda) \in \Omega^0(\epsilon)$ is a global minimum point of $L_a(x,\lambda;\epsilon)$, then $\bar x$ is a global minimum point for Problem (1) and $\bar\lambda$ is the corresponding multiplier, and conversely.*

From the definition and the differentiability assumptions on f and g, it follows that the function $L_a(x,\lambda;\epsilon)$ is an SC^1 function for all $(x,\lambda) \in \mathcal{P} \times \mathrm{I\!R}^m$, that is a continuously differentiable function with a semismooth gradient (see [25]). The gradient of L_a is given by:

$$\begin{aligned}
\nabla_x L_a(x,\lambda;\epsilon) &= \nabla_x L(x,\lambda) + \frac{1}{\epsilon p(x,\lambda)} \nabla g(x) \max\{g(x), -\epsilon p(x,\lambda)\lambda\} \\
&+ \frac{s}{2\epsilon a(x) p(x,\lambda)} \| \max\{g(x), -\epsilon p(x,\lambda)\lambda\}\|^2 \sum_{i=1}^m \nabla g_i(x) \max\{g_i(x), 0\}^{s-1} \\
&+ 2\left[\nabla_x^2 L(x,\lambda)\nabla g(x) + \sum_{i=1}^m \nabla^2 g_i(x) \nabla_x L(x,\lambda) e_i' + 2\nabla g(x) G(x)\Lambda\right] \left[M(x)\lambda + \nabla g(x)'\nabla f(x)\right], \\
\nabla_\lambda L_a(x,\lambda;\epsilon) &= \max\{g(x), -\epsilon p(x,\lambda)\lambda\} + \frac{1}{\epsilon a(x)} \; \| \max\{g(x), -\epsilon p(x,\lambda)\lambda\}\|^2 \lambda \\
&+ 2M(x) \left[M(x)\lambda + \nabla g(x)'\nabla f(x)\right]
\end{aligned}$$

where $M(x)$ is given by

$$M(x) \quad = \quad \nabla g(x)'\nabla g(x) + G^2(x), \tag{5}$$

and e_i denotes the ith column of the $m \times m$ identity matrix.

Since L_a is an SC^1 function in $\mathcal{P} \times \mathrm{I\!R}^m$, its generalized Hessian $\partial^2 L_a(x,\lambda;\epsilon)$, in Clarke's sense, can be defined [3]. For SC^1 functions a second-order Taylor-like expansion is possible, as stated in the following proposition.

Proposition 2.2 (See [18]) *Let $h : \mathrm{I\!R}^n \to \mathrm{I\!R}$ be an SC^1 function on the open set $\mathcal{O}$ and let x and y be two points in $\mathcal{O}$ such that $[x,y]$ is contained in $\mathcal{O}$. Then*

$$h(y) = h(x) + \nabla h(x)'(y-x) + \frac{1}{2}(y-x)'\Phi(y-x),$$

for some $\Phi \in \partial^2 h(z)$ and for some $z \in (x,y)$, where $\partial^2 h$ denotes the generalized Hessian of h.

By exploiting the piecewise smooth structure of the gradient of L_a, it is possible to describe the structure of the generalized Hessian $\partial^2 L_a$ in a neighborhood of a KKT pair of Problem (1). To this aim we consider a partition of the index set $\{1,\dots,m\}$ into the subsets $A \subseteq \{1,\dots,m\}$, $N = \{1,\dots,m\}\setminus A$, and we partition the vectors g and λ according to these index sets: $g = (g_A' \; g_N')'$ and $\lambda = (\lambda_A' \; \lambda_N')'$. Then we introduce the $(n+m)\times(n+m)$ symmetric matrix $H(x,\lambda;\epsilon,A)$ given block-wise by:

$$H_{xx}(x,\lambda;\epsilon,A) = \nabla_x^2 L(x,\lambda) + \frac{1}{\epsilon p(x,\lambda)}\nabla g_A(x)\nabla g_A(x)' + 2\nabla_x^2 L(x,\lambda)\nabla g(x)\nabla g(x)'\nabla_x^2 L(x,\lambda),$$

$$\begin{aligned} H_{x\lambda}(x,\lambda;\epsilon,A) &= \begin{bmatrix}\nabla g_A(x) & 0\end{bmatrix} + 2\nabla_x^2 L(x,\lambda)\nabla g(x) M_N(x), \\ H_{\lambda\lambda}(x,\lambda;\epsilon,A) &= -\epsilon p(x,\lambda)\begin{bmatrix}0 & 0\\ 0 & I_N\end{bmatrix} + 2M_N(x)M_N(x), \end{aligned} \tag{6}$$

where

$$M_N(x) = \nabla g(x)'\nabla g(x) + \begin{pmatrix}0 & 0\\ 0 & G_N(x)^2\end{pmatrix}, \tag{7}$$

I_N is the identity matrix of dimension $|N|$ and 0 is a zero matrix of proper dimensions.
In correspondence of a KKT pair $(\bar{x},\bar{\lambda})$ we define the index set of the strictly active constraints, namely $A_+(\bar{x},\bar{\lambda}) = \{j \in A_0(\bar{x}) : \;\; \bar{\lambda}_j > 0\}$.

Proposition 2.3 (See [9], Proposition 6.1) *For every KKT pair $(\bar{x},\bar{\lambda})$ of Problem (1) and every given ϵ, a neighborhood $\mathcal{B}$ of $(\bar{x},\bar{\lambda})$ exists such that, for all (x,λ) in $\mathcal{B}$, we have $\partial^2 L_a(x,\lambda;\epsilon) = \mathrm{co}\{\partial_B^2 L_a(x,\lambda;\epsilon)\}$, where:*

$$\partial_B^2 L_a(x,\lambda;\epsilon) = \{H(x,\lambda;\epsilon,A) + K(x,\lambda;\epsilon,A) : \;\; A \in \mathcal{A}\},$$

with

$$\mathcal{A} = \{A : \;\; A_+(\bar{x},\bar{\lambda}) \subseteq A \subseteq A_0(\bar{x})\},$$

$H(x,\lambda;\epsilon,A)$ is given by (6) and $K(x,\lambda;\epsilon,A)$ is a matrix such that $\|K(x,\lambda;\epsilon,A)\| \le \zeta(x,\lambda)$, with $\zeta(x,\lambda)$ a nonnegative continuous function such that $\zeta(\bar{x},\bar{\lambda}) = 0$.

We note that at a KKT pair where the strict complementarity holds, $A_+(\bar{x},\bar{\lambda}) = A_0(\bar{x})$, and $\partial^2 L_a(\bar{x},\bar{\lambda};\epsilon)$ reduces to a singleton; therefore in this case the generalized Hessian can be further characterized in a neighborhood of the KKT pair.

Proposition 2.4 (See [9], Proposition 6.2) *For every KKT pair $(\bar{x},\bar{\lambda})$ of Problem (1) where the strict complementarity holds, and for every given ϵ, a neighborhood $\mathcal{B}$ of $(\bar{x},\bar{\lambda})$ exists such that, for all (x,λ) in $\mathcal{B}$, L_a is twice continuously differentiable, with Hessian matrix given by:*

$$\nabla^2 L_a(x,\lambda;\epsilon) = H(x,\lambda;\epsilon,A_0(\bar{x})) + K(x,\lambda;\epsilon,A_0(\bar{x})),$$

where H and K are matrices like in Proposition 2.3.

The next proposition provides a basis for the construction of an algorithm converging to second order stationary points of Problem (1).

Proposition 2.5 (See [8]) *Let $(\bar{x},\bar{\lambda})$ be a KKT pair of Problem (1) and let $\epsilon > 0$ be given. If a positive semidefinite matrix $W \in \partial_B^2 L_a(\bar{x},\bar{\lambda};\epsilon)$ exists, then the pair $(\bar{x},\bar{\lambda})$ satisfies the second order necessary conditions (3).*

The exactness properties of the augmented Lagrangian function L_a, described in the previous section, give us the possibility of defining constrained minimization algorithms by drawing inspiration from the approaches developed in the field of unconstrained optimization. In particular, the merit function L_a allows us to extend the approach of defining curvilinear search algorithms in order to get global convergence towards second order stationary points.

However, as already pointed out in [14], this extension is not trivial since we must cope with the following difficulties:

- the correspondence between the stationary points of the augmented Lagrangian function L_a and the KKT pairs of the original constrained problem holds only for values of the penalty parameter ϵ smaller than the unknown threshold value $\bar{\epsilon}$; therefore any constrained optimization method, based on the minimization of the Lagrangian function L_a, must be able itself to locate suitable values of the penalty parameter;

- the augmented Lagrangian function L_a is not twice continuously differentiable everywhere and the evaluation of the second order derivatives, where they exist, requires the use of the third order derivatives of the functions f and g.

In this paper we describe a new primal-dual algorithm model by extending the approach proposed in [14], without requiring the third order derivatives of f and g. The algorithm is defined in the extended space of the primal-dual variables (x, λ). We denote the vector of the variable in the $n+m$ space as $z = (x',\ \lambda')'$ and all vectors are assumed partitioned accordingly.

3. Computation of the search direction

We begin this section by introducing the matrix Q^k defined as in [8], that is

$$Q^k = H(x^k, \lambda^k; \epsilon, A_{\oplus}^k), \tag{8}$$

where $H(x^k, \lambda^k; \epsilon, A_{\oplus}^k)$ is given by (6) and the set of indices $A_{\oplus}^k$ is such that a neighborhood $\mathcal{B}(\bar{x}, \bar{\lambda})$ of a KKT pair $(\bar{x}, \bar{\lambda})$ exists such that, for all $(x^k, \lambda^k) \in \mathcal{B}(\bar{x}, \bar{\lambda})$, $A_{\oplus}^k = A_0(\bar{x})$. We refer the reader to papers [12] and [13] for examples of sets $A_{\oplus}^k$ that satisfy the preceding requirement. We recall that, in the following, $d = (d_x',\ d_\lambda')'$.
The following proposition establishes the asymptotic connections between the matrix Q^k and the generalized Hessian at a first order stationary point of L_a.

Proposition 3.1. *Let $\{x^k, \lambda^k\}$ be a sequence converging to a first order stationary point $(\bar{x}, \bar{\lambda})$ of the function L_a and $\{Q^k\}$ a sequence of matrices defined by (8). Then,*

$$\lim_{k \to \infty} dist(Q^k | \partial_B^2 L_a(\bar{x}, \bar{\lambda}; \epsilon)) = 0.$$

Furthermore, for every sequence of matrices $\{W^k\}$, with $W^k \in \partial^2 L_a(x^k, \lambda^k; \epsilon)$, and every sequence of directions $\{d^k\}$, we have

$$d^{k\prime}(W^k - Q^k)d^k \le \delta^k,$$

where $\{\delta^k\}$ is a sequence of numbers converging to 0.

Proof. The proof easily follows from Proposition 2.3 and Proposition 5.1 in [8]. ◁

The main idea for computing the search direction for minimizing L_a consists in using an iterative scheme to solve the system

$$Q^k d = -\nabla L_a^k.$$

Thus, we apply the conjugate gradient method, as described in [15, 17], to the minimization of the quadratic form

$$q(d) = \frac{1}{2} d' Q^k d + \nabla L_a^{k\prime} d.$$

To simplify notation, in the remainder of this section we omit the iteration index k. Then, we recall that the conjugate gradient method either stops at the first iteration, thus producing $p^0 = -\nabla L_a$, or it performs m iterations, with $1 \leq m \leq n$, returning $m+1$ conjugate vectors with respect to matrix Q

$$p^0, p^1, \ldots, p^m.$$

Following the idea proposed in [15] for unconstrained optimization, given a number $\rho > 0$, we can define the following disjoint sets of indices

$$\begin{aligned} I_P &= \{i \leq m : p^{i\prime} Q p^i \geq \rho \|p^i\|^2\}, \\ I_S &= \{i \leq m : p^{i\prime} Q p^i \leq -\rho \|p^i\|^2\} \end{aligned}$$

which, in case $m \geq 1$, cannot be both empty. Let us define, at iteration k, the following directions

$$d_P = -\sum_{i \in I_P} \frac{\nabla L_a{}' p^i}{p^{i\prime} Q p^i} p^i, \tag{9}$$

$$d_S = -\sum_{i \in I_S} \frac{\nabla L_a{}' p^i}{|p^{i\prime} Q p^i|} p^i, \tag{10}$$

which, by definition, are such that:

$$d_P{}' Q d_P \geq 0, \tag{11}$$

$$d_S{}' Q d_S < 0, \tag{12}$$

therefore, d_P is a positive curvature direction whereas d_S is a negative curvature direction. The following proposition holds.

Proposition 3.2. *A constant $c > 0$ exists, such that*

$$\max\{\|d_P\|, \|d_S\|\} \leq c \|\nabla L_a\|. \tag{13}$$

Proof. The proof follows by considering point (b) of Theorem 2.2 in [17]. ◁

In order to guarantee convergence to second order stationary points, a modification of direction d_S is necessary. In particular, we consider a direction $\hat{d}_S$ obtained by adding to d_S another direction d_N, which is able to guarantee desired second order properties. Hence, let

$$\hat{d}_S = d_S + d_N$$

where d_N is such that the following Condition holds

Condition 1. *Directions d_N and $\hat{d}_S$ satisfies*

(a) $\nabla {L_a}' d_N \leq 0$ *and* $d'_N Q d_N < 0$;

(b) $\hat{d}'_S Q \hat{d}_S < 0$;

(c) *let* $\{d^k_S\}$, $\{d^k_N\}$ *and* $\{Q^k\}$ *be sequences of directions and matrices. Then,* $\{d^k_N\}$ *is bounded and, if* $\lim_{k\to\infty} \hat{d^k_S}' Q^k \hat{d}^k_S = 0$ *then* $\lim_{k\to\infty} \lambda_m(Q^k) = 0$.

We point out that a direction d_N satisfying Condition 1 can be computed in different ways, see, for example, [22, 19].

Let us now define

$$q(w) = \nabla {L_a}' w + 1/2 w' Q w.$$

Then, we show that directions d_P and $\hat{d}_S$ have some interesting properties.

Proposition 3.3. *Directions d_P and $\hat{d}_S$ are such that:*

- *if* $q(d_P) \leq q(\hat{d}_S)$, d_P *satisfies* $\nabla {L_a}' d_P \leq -\frac{1}{2\lambda_M(Q)} \|\nabla L_a\|^2$;
- *if* $q(d_P) > q(\hat{d}_S)$, $\hat{d}_S$ *satisfies* $q(\hat{d}_S) \leq -\frac{2}{3\lambda_M(Q)} \|\nabla L_a\|^2$.

Proof. Suppose first that $q(d_P) \leq q(\hat{d}_S)$. In this case, considering that ${d_P}' Q d_P \geq 0$ and $\hat{d_S}' Q \hat{d}_S < 0$, we have that

$$\nabla {L_a}' \hat{d}_S > q(\hat{d}_S) \geq q(d_P) \geq \nabla {L_a}' d_P. \tag{14}$$

Let us consider first the case when $I_S = \emptyset$. Then, considering that $p^0 = -\nabla L_a$,

$$\nabla {L_a}' d_P = -\sum_{i \in I_P} \frac{(\nabla {L_a}' p^i)^2}{{p^i}' Q p^i} \leq -\frac{(\nabla {L_a}' p^0)^2}{{p^0}' Q p^0} \leq -\frac{1}{\lambda_M(Q)} \|\nabla L_a\|^2.$$

Otherwise, if $I_S \neq \emptyset$, from (9), (14) and Theorem 2.2 of [17], it results

$$-\frac{1}{\lambda_M(Q)} \|\nabla L_a\|^2 \geq -\nabla {L_a}' \left(\sum_{i \in I_S} \frac{\nabla {L_a}' p^i}{|{p^i}' Q p^i|} p^i + \sum_{i \in I_P} \frac{\nabla {L_a}' p^i}{{p^i}' Q p^i} p^i \right) \geq 2 \nabla {L_a}' d_P.$$

Consider now the case when $q(d_P) > q(\hat{d}_S)$. By (9) we have that

$$\begin{aligned} q(\hat{d}_S) &< \nabla {L_a}' d_P + \frac{1}{2} {d_P}' Q d_P = \nabla {L_a}' d_P + \frac{1}{2} \sum_{i \in I_P} \frac{(\nabla {L_a}' p^i)^2}{{p^i}' Q p^i} \\ &= \nabla {L_a}' d_P - \frac{1}{2} \nabla {L_a}' \left(-\sum_{i \in I_P} \frac{(\nabla {L_a}' p^i)}{{p^i}' Q p^i} p^i \right) = \frac{1}{2} \nabla {L_a}' d_P. \end{aligned} \tag{15}$$

On the other hand, by points (a) and (b) of Condition 1, we know that

$$q(\hat{d}_S) \leq \nabla {L_a}' \hat{d}_S. \tag{16}$$

From relations (15) and (16) we get that

$$\frac{3}{2}q(\hat{d}_S) \leq \frac{1}{2}\nabla {L_a}'(d_P + \hat{d}_S)$$

which , by (9), (10) and Theorem 2.2 in [17], implies that

$$\frac{3}{2}q(\hat{d}_S) \leq -\frac{1}{\lambda_M(Q)}\|\nabla L_a\|^2.$$

which completes the proof. ◁

4. The adaptive linesearch ALS

In this section we focus our attention on the definition of a suitable linesearch scheme. The procedure, given the two directions d_P and $\hat{d}_S$, selects one of them and performs a suitable linesearch along it. For this reason we call the procedure adaptive linesearch (ALS). We show that ALS is able to enforce convergence towards stationary points of the augmented Lagrangian function L_a assuming that ϵ stays fixed. The problem of adjusting the value of the penalty parameter and the convergence towards second order stationary points of the original constrained problem will be addressed in the next section.

To simplify notation, we omit the iteration index k whenever it is unnecessary.

For a fixed value of the penalty parameter ϵ, the adaptive linesearch ALS takes as input $(x, \lambda) = z \in \Omega^0(\epsilon)$, the values $L_a = L_a(x, \lambda; \epsilon)$, $\nabla L_a = \nabla L_a(x, \lambda; \epsilon)$, the directions $d_P, \hat{d}_S$ and computes a matrix $Q \in \mathbb{R}^{(n+m)\times(n+m)}$, and it gives in output the point $(\hat{x}, \hat{\lambda}) = \hat{z} \in \Omega^0(\epsilon)$.

Adaptive linesearch: ALS$(x, \lambda, d_P, \hat{d}_S; \epsilon)$

Step 0. **Data**. constants $\beta \in (0,1)$, $\sigma > 0$ and $\mu \in (0, \frac{1}{2})$ are given.

Step 1. **Choice of the search direction**.
If $q(d_P) \leq q(\hat{d}_S)$ **Then** *go to Step 2.* **Else** *go to Step 3.*

Step 2. **Linesearch along a gradient-related direction**.
Set $d = d_P$ *and compute* $\eta = \beta^\ell$ *where* ℓ *is the smallest nonnegative integer such that*

$$L_a(z + \eta d; \epsilon) \leq L_a(z; \epsilon) + \mu\eta \nabla L_a{}' d \quad \text{and} \quad x + \eta d_x \in \mathcal{P}, \tag{17}$$

and go to Step 4.

Step 3. **Linesearch along a negative curvature direction**.
Set $d = \hat{d}_S$ *and compute* Q. *If*

$$L_a(z + \sigma d; \epsilon) \leq L_a(z; \epsilon) + \mu \left(\sigma \nabla L_a{}' d + \frac{1}{2}(\sigma)^2 d' Q d \right) \quad \textit{and} \quad x + \sigma d_x \in \mathcal{P}, \tag{18}$$

compute $\eta = \beta^\ell \sigma$, *where* ℓ *is the largest non-positive integer such that*

$$L_a(z + \eta d; \epsilon) \leq L_a(z; \epsilon) + \mu \left(\eta \nabla L_a{}' d + \frac{1}{2}(\eta)^2 d' Q d \right) \quad \text{and} \quad x + \eta d_x \in \mathcal{P}, \tag{19}$$

and

$$L_a(z + \frac{\eta}{\beta} d; \epsilon) > L_a(z; \epsilon) + \mu \left(\frac{\eta}{\beta} \nabla L_a{}' d + \frac{1}{2} \left(\frac{\eta}{\beta}\right)^2 d' Q d \right) \quad \text{or} \quad x + \frac{\eta}{\beta} d_x \notin \mathcal{P}. \tag{20}$$

Otherwise compute $\eta = \beta^\ell \sigma$, *where* ℓ *is the smallest positive integer such that (19) holds.*

Step 4. **Update**. *Set* $\hat{z} = z + \eta d$ *and return* $\hat{z}$.

We note that the adaptive linesearch ALS differs from unconstrained curvilinear searches for the fact that the trial points are accepted only if the x-component belongs to $\mathcal{P}$. The matrix Q plays a role similar to the role played by the Hessian matrix in the unconstrained algorithms and it is given by (8), as it has been shown in Section 3, so as to provide some kind of second order information on the original constrained problem to the algorithm.

First we prove that ALS is well-defined.

Proposition 4.1. *For any fixed value* ϵ, *let the directions* d_P, $\hat{d}_S$ *and the matrices* Q *be defined as in Section 3. Then procedure ALS returns a value* $\eta > 0$.

Proof. We proceed by considering the two cases (i) $\nabla L_a(z; \epsilon) \neq 0$ and (ii) $\nabla L_a(z; \epsilon) = 0$.

(i) In case procedure ALS selects direction d_P, the result follows from standard arguments of Armijo-type linesearch along a descent direction.

Otherwise, if procedure ALS selects direction $\hat{d}_S$. If (18) is satisfied, the existence of a finite l is implied by (19) and the compactness of the level set $\Omega_0(\epsilon)$. Assume now that (18) fails. We note that $\mathcal{P}$ is an open set, therefore the test $x + \eta d_x \in \mathcal{P}$ is satisfied for sufficiently small values of η. Moreover, by Proposition 2.2, we can write

$$L_a(z + \eta d; \epsilon) = L_a(z; \epsilon) + \eta \nabla L_a(z; \epsilon)' \hat{d}_S + \frac{1}{2}\eta^2 (\hat{d}_S)' W \hat{d}_S \tag{21}$$

for some symmetric matrix W belonging to $\partial^2 L_a(u; \epsilon)$ where $u = z + \omega\eta\hat{d}_S$ for some $\omega \in (0, 1)$.

Now assume, by contradiction, that a sequence $\{\eta^j\}$ exists such that $\eta^j \to 0$ for $j \to \infty$ and

$$L_a\left(z + \eta^j d; \epsilon\right) > L_a(z; \epsilon) + \mu\eta^j \nabla L_a(z; \epsilon)' \hat{d}_S + \mu\frac{1}{2}(\eta^j)^2 \hat{d}_S' Q \hat{d}_S. \tag{22}$$

By considering (21), we get

$$0 > (\mu - 1)\eta^j \nabla L_a(z; \epsilon)' \hat{d}_S - \frac{1}{2}(\eta^j)^2 \hat{d}_S' W \hat{d}_S + \mu\frac{1}{2}(\eta^j)^2 \hat{d}_S' Q \hat{d}_S. \tag{23}$$

Dividing (23) by η^j and taking the limit for $j \to \infty$, we get

$$(\mu - 1)\nabla L_a(z; \epsilon)' \hat{d}_S \leq 0$$

which contradicts Proposition 3.2.

(ii) Let us now suppose that $\nabla L_a(z; \epsilon) = 0$. In this case, by Proposition 3.2, we have that $d_P = 0$ and $\hat{d}_S = d_N$. By Condition 1, procedure ALS selects $\hat{d}_S$ so that it results $\hat{d}_S' Q \hat{d}_S < 0$. Again, if relation (18) is satisfied, the existence of a finite l is guaranteed by (19) and the compactness of the level set $\Omega_0(\epsilon)$.

Otherwise, assume that (18) is not satisfied. By the fact that $\mathcal{P}$ is an open set, it follows that $x + \eta d \in \mathcal{P}$ for η sufficiently small. In case $\nabla L_a(z; \epsilon) = 0$, by Proposition 2.2, we can write

$$L_a(z + \eta d; \epsilon) = L_a(z; \epsilon) + \frac{1}{2}\eta^2 (\hat{d}_S)' W^j \hat{d}_S \tag{24}$$

for some symmetric matrix W^j belonging to $\partial^2 L_a(u; \epsilon)$ where $u = z + \omega\eta\hat{d}_S$ for some $\omega \in (0, 1)$.

Assume, by contradiction, that a sequence $\{\eta^j\}$ exists such that $\eta^j \to 0$ for $j \to \infty$ and

$$L_a\left(z + \eta^j d; \epsilon\right) > L_a(z; \epsilon) + \mu\frac{1}{2}(\eta^j)^2 \hat{d}_S' Q \hat{d}_S. \tag{25}$$

By considering (24) and (25) we get

$$0 > -\frac{1}{2}(\eta^j)^2 \hat{d}_S' W^j \hat{d}_S + \mu\frac{1}{2}(\eta^j)^2 \hat{d}_S' Q \hat{d}_S,$$

which, dividing both sides by $(\eta^j)^2/2$ and by adding and subtracting $\hat{d}_S' Q \hat{d}_S$, gives

$$0 < \hat{d}_S'(W^j - Q)\hat{d}_S + (1 - \mu)\hat{d}_S' Q \hat{d}_S.$$

Now, considering Proposition 3.1 we get

$$0 < (1-\mu)\hat{d}_S{}'Q\hat{d}_S + \delta^j \tag{26}$$

where $\delta^j \to 0$ since $z + \eta^j d \to z$ where $\nabla L_a(z;\epsilon) = 0$. Taking the limit for $j \to \infty$ in (26) we obtain

$$0 < (1-\mu)\hat{d}_S{}'Q\hat{d}_S$$

which contradicts the assumption that when $\nabla L_a(z;\epsilon) = 0$ then $(\hat{d}_S)'Q\hat{d}_S < 0$. ◁

In the following we denote by $(x^{k+1}, \lambda^{k+1}) = ALS(x^k, \lambda^k, d_P^k, \hat{d}_S^k; \epsilon)$ the new point produced by ALS for a given value of ϵ and we show that ALS is able to produce a sequence of points $\{(x^k, \lambda^k)\}$ globally convergent towards stationary points of the augmented Lagrangian function L_a. The overall algorithm SOLA converging to second order stationary points and including the adjustment rule for ϵ is discussed in section 5.

Now, we can prove the following result.

Proposition 4.2. *For any fixed value ϵ, let the directions d_P^k and $\hat{d}_S^k$ be defined as in Section 3. Let $\{x^k, \lambda^k\}$ be an infinite sequence produced by procedure ALS, then*

$$\lim_{k\to\infty} \nabla L_a(x^k, \lambda^k; \epsilon) = 0. \tag{27}$$

Moreover, if Q^k is given by (8), then for every infinite index set $\bar{K}$ such that $d^k = \hat{d}_S^k$ for all $k \in \bar{K}$

$$\lim_{k\to\infty, k\in\bar{K}} (\hat{d}_S^k)'Q^k\hat{d}_S^k = 0. \tag{28}$$

Proof. By the compactness of the level set $\Omega_0(\epsilon)$, we have that sequence $\{x^k, \lambda^k\}$ admits a limit point $(\bar{x}, \bar{\lambda})$. Let K_s and K_d be index sets of two subsequences of iterates converging to $(\bar{x}, \bar{\lambda})$ such that

(i) $d^k = d_P^k$ for all $k \in K_d$ and (17) holds;

(ii) $d^k = \hat{d}_S^k$ for all $k \in K_s$ and (19) holds.

By (17) and (19) we know that the sequence $\{L_a(x^k, \lambda^k; \epsilon)\}$ is non-increasing which considering the compactness of $\Omega_0(\epsilon)$ yields that $\{L_a(x^k, \lambda^k; \epsilon)\}$ admits a limit point.
In order to prove that $\nabla L_a(\bar{x}, \bar{\lambda}; \epsilon) = 0$ we proceed by contradiction. Suppose that $\|\nabla L_a(x^k, \lambda^k; \epsilon)\| > \tau > 0$ for all $k \in K_s \cup K_d$.
Suppose first that K_d is infinite. Then we have

$$|L_a(x^{k+1}, \lambda^{k+1}; \epsilon) - L_a(x^k, \lambda^k; \epsilon)| \geq \mu\eta^k|\nabla L_a(x^k, \lambda^k; \epsilon)'d_k|.$$

It follows that $\eta^k|\nabla L_a(x^k, \lambda^k; \epsilon)'d_k| \to 0$ as $k \to \infty$, $k \in K_d$. Therefore, either $\eta^k \to 0$ or $|\nabla L_a(x^k, \lambda^k; \epsilon)'d_k| \to 0$, as $k \to \infty$, $k \in K_d$.
Suppose first that $\eta^k \to 0$, as $k \to \infty$, $k \in K_d$. Since

$$L_a\left(z^k + \frac{\eta^k}{\beta}d_k; \epsilon\right) - L_a(z_k; \epsilon) > \mu\frac{\eta^k}{\beta}\nabla L_a^{k\prime} d_k,$$

then, by the mean value theorem we have, for $k \in K_d$,

$$\frac{\eta^k}{\beta}\nabla L_a(z^k + \delta\frac{\eta^k}{\beta}d_P^k;\epsilon)' d_k > \mu\frac{\eta^k}{\beta}\nabla L_a^{k\prime} d_P^k,$$

for some $\delta \in (0,1)$. Dividing by η^k/β and by $\|d_k\|$, we obtain

$$\frac{\nabla L_a(z^k + \delta\frac{\eta^k}{\beta}d_P^k;\epsilon)' d_P^k}{\|d_P^k\|} > \mu\frac{\nabla L_a^{k\prime} d_P^k}{\|d_P^k\|} \tag{29}$$

for $k \in K_d$. Now, we can extract a subsequence whose indices lie in the set $K_d' \subseteq K_d$ such that

$$z^k \to \bar{z} \quad \text{and} \quad \frac{d_P^k}{\|d_P^k\|} \to \bar{d}$$

for $k \in K_d'$. From (29), taking the limit as $k \to \infty, k \in K_d'$ we obtain that

$$(1-\mu)\nabla L_a(\bar{z};\epsilon)'\bar{d} \geq 0.$$

Since $1-\mu > 0$ and $(\nabla L_a^k)' d_P^k < 0$ for all $k \in K_d'$ we have that $\nabla L_a(\bar{z};\epsilon)'\bar{d} = 0$ which implies, by using Proposition 3.3, $\nabla L_a(\bar{z};\epsilon) = 0$ and this contradicts the fact that $\|\nabla L_a^k\| > \tau > 0$. Hence η^k cannot tend to zero for $k \in K_d$. This implies that there exists a subsequence $K_d'' \subseteq K_d$ such that $\left|(\nabla L_a^k)' d_P^k\right| \to 0$ as $k \to \infty, k \in K_d''$. Proposition 3.3 and the continuity of the gradient imply that $\nabla L_a(\bar{z};\epsilon) = 0$, which again contradicts the assumption that $\|\nabla L_a^k\| > \tau > 0$. Hence this latter assumption is itself impossible and we conclude that $\nabla L_a(\bar{z};\epsilon) = 0$ whenever K_d is infinite.

Now, suppose that K_s is infinite. In this case, it follows from (19) that

$$\left|L_a(z^{k+1};\epsilon) - L_a(z^k;\epsilon)\right| \geq \mu\left|\eta^k(\nabla L_a^k)'\hat{d}_S^k + \frac{1}{2}(\eta^k)^2(\hat{d}_S^k)' Q^k \hat{d}_S^k\right|.$$

for $k \in K_s$, and hence that

$$\left|\eta^k(\nabla L_a^k)'\hat{d}_S^k + \frac{1}{2}(\eta^k)^2(\hat{d}_S^k)' Q^k \hat{d}_S^k\right| \to 0 \quad \text{as} \quad k \to \infty.$$

Therefore, either

$$(\nabla L_a^k)'\hat{d}_S^k \to 0 \quad \text{and} \quad (\hat{d}_S^k)' Q^k \hat{d}_S^k \to 0 \quad (k \to \infty, k \in K_s) \tag{30}$$

or $\eta^k \to 0$ when $k \to \infty, k \in K_s$. If $\eta^k \to 0$, $k \to \infty, k \in K_s$, we have

$$L_a\left(z^k + \frac{\eta^k}{\beta}\hat{d}_S^k;\epsilon\right) - L_a(z^k;\epsilon) > \mu\left(\frac{\eta^k}{\beta}(\nabla L_a^k)'\hat{d}_S^k + \frac{1}{2}\left(\frac{\eta^k}{\beta}\right)^2(\hat{d}_S^k)^T Q^k \hat{d}_S^k\right),$$

which, by Proposition 2.2, can be rewritten as

$$\frac{\eta^k}{\beta}(\nabla L_a^k)'\hat{d}_S^k + \frac{1}{2}\frac{(\eta^k)^2}{\beta^2}(\hat{d}_S^k)' W^k \hat{d}_S^k > \mu\left(\frac{\eta^k}{\beta}(\nabla L_a^k)'\hat{d}_S^k + \frac{1}{2}\left(\frac{\eta^k}{\beta}\right)^2(\hat{d}_S^k)' Q^k \hat{d}_S^k\right) \tag{31}$$

for some $\delta \in (0,1)$, $k \in K_s$, and where W^k belonging to $\partial^2 L_a(u;\epsilon)$ where $u = (z^k + \delta\frac{\eta^k}{\beta}\hat{d}_S^k)$. From (31) and Condition 1 we obtain

$$0 \leq (\mu - 1)\left[(\nabla L_a^k)'\hat{d}_S^k + \frac{1}{2}\frac{\eta^k}{\beta}(\hat{d}_S^k)'Q^k\hat{d}_S^k\right] < \frac{1}{2}\frac{\eta^k}{\beta}(\hat{d}_S^k)'\left[W^k - Q^k\right]\hat{d}_S^k. \tag{32}$$

Taking the limit for $k \to \infty$, $k \in K^s$, in (32), we obtain that $(\nabla L_a^k)'\hat{d}_S^k \to 0$ which by Proposition 3.1 proves (27).
In order to prove the last part of the proposition, we note that $\bar{K} \subseteq K_s$. Therefore, considering that by Proposition 3.2 $(\nabla L_a^k)'\hat{d}_S^k < 0$ and recalling (32), we have

$$0 \leq (\mu - 1)\frac{1}{2}\frac{\eta^k}{\beta}(\hat{d}_S^k)'Q^k\hat{d}_S^k < \frac{1}{2}\frac{\eta^k}{\beta}(\hat{d}_S^k)'\left[W^k - Q^k\right]\hat{d}_S^k.$$

Taking the limit in the above relation and by Proposition 3.1, we get the result. ◁

Now we report a technical result which will be used to prove convergence to second order stationary points of the overall algorithm. It basically states that in a neighborhood of KKT pair that does not satisfy the second order necessary optimality condition, Procedure ALS selects as search direction $\hat{d}_S^k$.

Proposition 4.3. *Let $\{(x^k,\lambda^k)\}_{\mathcal{K}}$ be a subsequence converging to $(x^\star,\lambda^\star)$ which is a KKT pair of Problem (1) that does not satisfy the second order necessary optimality condition. Let $\{\hat{d}_S^k\}$ be a sequence of directions satisfying Condition 1, let $\{d_P^k\}$ and $\{Q^k\}$ be sequences of direction and matrices, respectively, given by (9) and (8). Then, for $k \in \mathcal{K}$ and sufficiently large, Step 1 of Procedure ALS selects*

$$d^k = \hat{d}_S^k.$$

Proof. Let us assume that the sequence $\{(x^k,\lambda^k)\}_{\mathcal{K}}$ converges to $(x^\star,\lambda^\star)$ which is a stationary point of Problem (1) that does not satisfy the second order necessary optimality condition. Then it is our aim to prove that, for $k \in \mathcal{K}$ and k sufficiently large,

$$q(\hat{d}_S^k) < q(d_P^k),$$

so that $d^k = d_S^k$.
First of all, we note that, by construction of d_P^k,

$$q(d_P^k) = \nabla L_a^{k'} d_P^k + \frac{1}{2}d_P^{k'}Q^k d_P^k \geq \nabla L_a^{k'} d_P^k.$$

Therefore, by Proposition 3.3,

$$\lim_{k\to\infty, k\in K} q(d_P^k) \geq 0. \tag{33}$$

Analogously, we have

$$q(\hat{d}_S^k) = \nabla L_a^{k'}\hat{d}_S^k + \frac{1}{2}(\hat{d}_S^k)'Q^k\hat{d}_S^k.$$

Since $\{(x^k,\lambda^k)\}_{\mathcal{K}}$ is converging to a KKT pair $(x^\star,\lambda^\star)$ which does not satisfy the second order necessary optimality conditions, by Proposition 2.5, we have that every matrix $W \in \partial_B^2 L_a(\bar{x},\bar{\lambda};\epsilon)$ is such that $\lambda_m(W) < 0$. Now, by Proposition 3.1 and for $k \in K$ sufficiently large, $\lambda_m(Q^k) < 0$ as well.

By Proposition 3.2 and Condition 1, it follows that $\hat{d}_S^k$ is bounded and $\nabla L_a^{k\prime} \hat{d}_S^k \to 0$ as $k \in K$ tends to ∞. Hence, by point (c) of Condition 1,

$$\lim_{k\in K, k\to\infty} q(\hat{d}_S^k) = \lim_{k\in K, k\to\infty} \frac{1}{2} (\hat{d}_S^k)' Q^k \hat{d}_S^k < 0,$$

which, along with relation (33), completes the proof. ◁

5. The overall algorithm SOLA

In this section we show that it is possible to update in a simple way the penalty parameter ϵ while minimizing the augmented Lagrangian function L_a. We show that, under some additional conditions on d_P^k, d_S^k and Q^k, the limit points generated by Algorithm SOLA are also second order stationary points of Problem (1). This motivates the name SOLA, which stands for Second Order Lagrangian Algorithm. In the algorithm we make use of the adaptive linesearch scheme ALS described in section 4. We recall that ALS accepts as inputs (x^k, λ^k), $L_a(x^k, \lambda^k; \epsilon)$, $\nabla L_a(x^k, \lambda^k; \epsilon)$, $d_P^k, \hat{d}_S^k, Q^k$. We denote the new point (x^{k+1}, λ^{k+1}) by $ALS(x^k, \lambda^k, d_P^k, \hat{d}_S^k; \epsilon)$.

Algorithm SOLA (Second Order Augmented Lagrangian Algorithm)

Data: $(y^0, \mu^0) \in \mathbb{R}^n \times \mathbb{R}^m$, and $\epsilon^0 > 0$. Choose $\alpha > 0$ and $s \geq 3$ such that $y^0 \in \mathcal{P}$.

Step 0: Set $j = 0$ and $(x^0, \lambda^0) = (y^0, \mu^0)$ `(outer iteration)`.

Step 1: Set $k = 0$ `(inner iteration)`.

While (Stopping condition not satisfied) **do**

> **If** $\|\nabla L_a(x^k, \lambda^k; \epsilon^j)\| \geq \| \max\{g(x^k), -\epsilon^j p(x^k, \lambda^k)\lambda^k\}\|$ **then**
>
> > compute two directions d_P^k and $\hat{d}_S^k$
> > compute $(x^{k+1}, \lambda^{k+1}) = ALS(x^k, \lambda^k, d_P^k, \hat{d}_S^k; \epsilon^j)$
> > set $k = k + 1$;
>
> **else** `(update` ϵ `and restart the inner iteration)`
>
> > Set $\epsilon^{j+1} \in (0, \epsilon^j)$, $(y^{j+1}, \mu^{j+1}) = (x^k, \lambda^k)$, $j = j + 1$.
> > **If** $L_a(y^j, \mu^j; \epsilon^j) \leq L_a(y^0, \mu^0; \epsilon^j)$ set $(x^0, \lambda^0) = (y^j, \mu^j)$
> > **else** set $(x^0, \lambda^0) = (y^0, \mu^0)$.
> > Go to Step 1.
>
> **End If**

End while

Algorithm SOLA can be seen as an enhancement of algorithm ALFA, proposed in [9]. In the definition of ALFA, an iteration map $T[z^k]$ which returns the value z^{k+1} is used; T must be such that, for every fixed value of ϵ and every starting point $z^0 \in \mathcal{P} \times \mathbb{R}^m$, the sequence $\{z^k\}$ belongs to the level set $\Omega(z^0, \epsilon)$ and all limits points are stationary points of L_a (Assumption A4 of [9]). This requirement is satisfied by ALS by Proposition 4.1. Hence, in the convergence analysis of SOLA, we can use part of the analysis developed for ALFA.

Proposition 5.1. *Let $\{x^k, \lambda^k\}$ be a sequence converging to a KKT pair $(\bar{x}, \bar{\lambda})$ of Problem (1). Let matrix Q^k be given by (8) and the directions $\hat{d}_S^k$ and d_N^k satisfy Condition 1. If*

$$\lim_{k\to\infty} (\hat{d}_S^k)' Q^k \hat{d}_S^k = 0,$$

then $(\bar{x}, \bar{\lambda})$ satisfies the second order necessary conditions for Problem (1).

Proof. The proof follows from point (c) of Condition 1, Proposition 2.5 and Proposition 3.1. ◁

The following proposition establishes the main result of this paper.

Proposition 5.2. *Let the matrices Q^k and the directions d_P^k, $\hat{d}_S^k$ used in procedure ALS, be defined as in Section 3. Then, after having updated the penalty parameter ϵ at most a finite number of times, Algorithm SOLA produces an infinite sequence $\{(x^k, \lambda^k)\}$ such that every limit point (x^*, λ^*) of $\{(x^k, \lambda^k)\}$ is a KKT pair of Problem (1) which satisfies SONC.*

Proof. Convergence of the sequence $\{(x^k, \lambda^k)\}$ generated by Algorithm SOLA to KKT pairs of Problem 1 follows using the same arguments of the convergence analysis of algorithm ALFA of [9]. Actually SOLA differs from ALFA in the use of procedure ALS. By Proposition 4.2 ALS satisfies Assumption A4 of [9] required by Algorithm ALFA on the iteration map T. Hence, using Theorem 7.2 of [9], we have that the penalty parameter is updated at most a finite number of times. Hence, by Proposition 4.1 we have that the sequence produced by Algorithm SOLA converges to a KKT pair (x^*, λ^*) of Problem (1).
In order to prove convergence to a point that satisfies SONC we proceed by contradiction and suppose that an infinite index set $\mathcal{K}$ exists such that

$$\{(x^k, \lambda^k)\}_{\mathcal{K}} \to (\bar{x}, \bar{\lambda})$$

with $(\bar{x}, \bar{\lambda})$ a KKT pair of Problem (1) which does not satisfy SONC. By Proposition 4.3, we know that for k sufficiently large, $k \in \mathcal{K}$, $d^k = \hat{d}_S^k$ in procedure ALS. Hence, by Proposition 4.2, it results

$$\lim_{k\to\infty, k\in\mathcal{K}} (\hat{d}_S^k)' Q^k \hat{d}_S^k = 0,$$

which contradicts Proposition 5.1, thus proving the result. ◁

Finally, we point out that far from a KKT pair, namely whenever

$$\|\nabla L_a(x^k, \lambda^k; \epsilon)\| + \|\max\{g(x^k), -\epsilon p(x^k, \lambda^k)\lambda^k\}\|$$

is large, we can also set $\hat{d}_S^k = d_S^k$, namely we can set $d_N^k = 0$, in Algorithm SOLA, since we can approach KKT pairs by using only the directions d_P^k and d_S^k.

6. Conclusions

In the paper we propose a method for the solution of inequality constrained nonlinear programming problem which is globally convergent to KKT pairs that satisfy second order necessary optimality conditions. The algorithm hinges on the idea of comparing, at every iteration, the relative effects of two directions and the selecting the more promising one. The selection rule is such that convergence to second order stationary points can be guaranteed. In the paper we do not concentrate on the analysis of the convergence rate of the overall Algorithm SOLA. Showing that SOLA is superlinear convergent is straightforward and can be done by using analogous reasoning as in the paper [7].

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