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Maitine Bergounioux, Mounir Haddou

► To cite this version:

Maitine Bergounioux, Mounir Haddou (Dir.). A SQP-Augmented Lagrangian Method for Optimal Control of Semilinear Elliptic Variational Inequalities. Desch. Birkhauser, pp. 58-73, 2003. <hal-00022019>

HAL Id: hal-00022019

<https://hal.science/hal-00022019v1>

Submitted on 31 Mar 2006

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A SQP-Augmented Lagrangian Method for Optimal Control of Semilinear Elliptic Variational Inequalities

M. Bergounioux and M. Haddou

Abstract. We investigate optimal control problems governed by semilinear elliptic variational inequalities involving constraints on the control. We present an augmented Lagrangian method coupled with a Gauss-Seidel type splitting to solve a relaxed problem which is a good approximation of the genuine one. Implementation is based on SQP methods.

1. Introduction

The aim of this paper is to describe an efficient numerical method to solve an optimal control problem governed by a semilinear elliptic variational inequality. It is known that Lagrange multipliers may not exist for such problems [7]. Nevertheless, providing qualifications conditions, one can exhibit multipliers for relaxed problems. These multipliers usually allow to get optimality conditions of Karush-Kuhn-Tucker type. It is an essential tool to develop numerical algorithms, especially Lagrangian ones (coupled or not with SQP methods).

In this paper we describe a “continuous” algorithm and we give a convergence result. We do not care about the discretization process. We shall discuss finite dimensional methods for the discretized problem in a forthcoming paper together with a comparison with the method we present here.

Here we have to deal with the infinite dimensional frame and nonlinear problems: the study is more delicate but we get results that do not depend on the discretization process. The paper is organized as follows. We first describe the problem and recall some important results about Lagrange multipliers. Next section is devoted to the description of the algorithm, namely an augmented Lagrangian method with a Gauss-Seidel splitting as in [3, 6] and we give a convergence result; then, we describe different implementations for subproblems. In the last section, we discuss some numerical examples and propose some conclusions.

2. Problem Setting

Let Ω be an open, bounded subset of \mathbb{R}^n ($n \leq 3$) with a smooth boundary $\partial\Omega$. We shall denote $\|\cdot\|$ the $L^2(\Omega)$ -norm, $\langle \cdot, \cdot \rangle$ the duality product between $H^{-1}(\Omega)$ and $H_o^1(\Omega)$ and (\cdot, \cdot) the $L^2(\Omega)$ -inner product. Let us set

$$K = \{y \mid y \in H_o^1(\Omega), y \geq \psi \text{ a.e. in } \Omega\}. \quad (2.1)$$

where ψ is a $H^2(\Omega) \cap H_o^1(\Omega)$ function. It is a non empty, closed, convex subset of $H_o^1(\Omega)$.

In the sequel g is a non decreasing, \mathcal{C}^1 real-valued function such that g' is bounded, locally Lipschitz continuous and f belongs to $L^2(\Omega)$. Moreover, U_{ad} is a non empty, closed, convex subset of $L^2(\Omega)$.

For each v in U_{ad} we consider the following variational inequality problem : find $y \in K$ with

$$a(y, z) + G(y) - G(z) \geq (v + f, y - z) \quad \forall z \in K . \quad (2.2)$$

where G is a primitive function of g , and a is a bilinear form defined on $H_o^1(\Omega) \times H_o^1(\Omega)$ by

$$a(y, z) = \sum_{i,j=1}^n \int_{\Omega} a_{ij} \frac{\partial y}{\partial x_i} \frac{\partial z}{\partial x_j} dx + \sum_{i=1}^n \int_{\Omega} b_i \frac{\partial y}{\partial x_i} z dx + \int_{\Omega} c y z dx , \quad (2.3)$$

where a_{ij}, b_i, c belong to $L^\infty(\Omega)$. Moreover, we assume that a_{ij} belongs to $\mathcal{C}^{0,1}(\bar{\Omega})$ (the space of Lipschitz continuous functions in Ω) and that c is nonnegative. The bilinear form $a(\cdot, \cdot)$ is continuous on $H_o^1(\Omega) \times H_o^1(\Omega)$:

$$\exists M > 0, \forall (y, z) \in H_o^1(\Omega) \times H_o^1(\Omega) \quad a(y, z) \leq M \|y\|_{H_o^1(\Omega)} \|z\|_{H_o^1(\Omega)} \quad (2.4)$$

and is coercive :

$$\exists \nu > 0, \forall y \in H_o^1(\Omega), \quad a(y, y) \geq \nu \|y\|_{H_o^1(\Omega)}^2 . \quad (2.5)$$

We set A the elliptic differential operator from $H_o^1(\Omega)$ to $H^{-1}(\Omega)$ defined by

$$\forall (z, v) \in H_o^1(\Omega) \times H_o^1(\Omega) \quad \langle Ay, z \rangle = a(y, z) .$$

For any $v \in L^2(\Omega)$, problem (2.2) has a unique solution $y = y[v] \in H_o^1(\Omega)$. As the obstacle function belongs to $H^2(\Omega)$ we have an additional regularity result : $y \in H^2(\Omega) \cap H_o^1(\Omega)$ (see [1, 2]). Moreover (2.2) is equivalent to

$$Ay + g(y) = f + v + \xi, \quad y \geq \psi, \quad \xi \geq 0, \quad \langle \xi, y - \psi \rangle = 0, \quad (2.6)$$

where “ $\xi \geq 0$ ” stands for “ $\xi(x) \geq 0$ almost everywhere on Ω ”. The above equation is the optimality system for problem (2.2) : ξ is the multiplier associated to the constraint $y \geq \psi$. It is a priori an element of $H^{-1}(\Omega)$ but the regularity result for y shows that $\xi \in L^2(\Omega)$, so that $\langle \xi, y - \psi \rangle = \int_{\Omega} \xi (y - \psi)$.

Applying the simple transformation $y^* = y - \psi$, we may assume that $\psi = 0$ in the sequel. Of course functions g and f are modified as well, but their generic properties (local lipschitz-continuity, monotonicity) are not changed . Therefore we keep the same notations. Now, let us consider the optimal control problem defined as follows :

$$\min \left\{ J(y, v) \stackrel{def}{=} \frac{1}{2} \int_{\Omega} (y - z_d)^2 dx + \frac{\alpha}{2} \int_{\Omega} (v - v_d)^2 dx \mid y = y[v], v \in U_{ad}, y \in K \right\},$$

where $z_d, v_d \in L^2(\Omega)$ and $\alpha > 0$ are given quantities.

This problem is equivalent to the problem governed by a state equation (instead of inequality) with mixed state and control constraints:

$$\min \left\{ J(y, v) = \frac{1}{2} \int_{\Omega} (y - z_d)^2 dx + \frac{\alpha}{2} \int_{\Omega} (v - v_d)^2 dx \right\}, \quad (\mathcal{P})$$

$$Ay + g(y) = f + v + \xi \text{ in } \Omega, \quad y = 0 \text{ on } \Gamma, \quad (2.7)$$

$$(y, v, \xi) \in \mathcal{D}, \quad (2.8)$$

where

$$\mathcal{D} = \{(y, v, \xi) \in H_o^1(\Omega) \times L^2(\Omega) \times L^2(\Omega) \mid v \in U_{ad}, y \geq 0, \xi \geq 0, (y, \xi) = 0\}. \quad (2.9)$$

There exists at least an optimal solution $(\bar{y}, \bar{v}, \bar{\xi}) \in (H^2(\Omega) \cap H_o^1(\Omega)) \times L^2(\Omega) \times L^2(\Omega)$ to this problem (see [1, 2]). We cannot ensure the existence of Lagrange multipliers. This problem is a non qualified problem (in the usual KKT sense) because the interior of the feasible set \mathcal{D} is usually empty even for weak topology. One can find in [7] finite and infinite dimensional counterexamples. The problem turns to be qualified if the bilinear constraint $(y, \xi) = 0$ is relaxed in $(y, \xi) \leq \varepsilon$. So, following [2] we rather study the problem

$$(\mathcal{P}_\varepsilon) \quad \begin{cases} \min J(y, v) \\ Ay + g(y) = f + v + \xi \text{ in } \Omega, \quad y \in H_o^1(\Omega), \\ (y, v, \xi) \in \mathcal{D}_\varepsilon \end{cases}$$

$$\mathcal{D}_{\varepsilon, R} = \{(y, v, \xi) \in H_o^1(\Omega) \times L^2(\Omega) \times L^2(\Omega) \mid v \in U_{ad}, y \geq 0, \xi \geq 0, (y, \xi) \leq \varepsilon, \|\xi\| \leq R\}$$

where R is fixed, such that $R \geq \|\bar{\xi}\|$ and $\varepsilon > 0$. We denote $V_{ad} = \{\xi \in L^2(\Omega) \mid \xi \geq 0, \|\xi\| \leq R\}$ which is obviously a closed, convex subset of $L^2(\Omega)$. We proved in [2] that problem $(\mathcal{P}_\varepsilon)$ has at least one optimal solution $(y_\varepsilon, v_\varepsilon, \xi_\varepsilon)$. Moreover, for $\varepsilon \rightarrow 0$, we have that y_ε converges to \tilde{y} strongly in $H_o^1(\Omega)$, v_ε converges to \tilde{v} strongly in $L^2(\Omega)$, ξ_ε converges to $\tilde{\xi}$ weakly in $L^2(\Omega)$, where $(\tilde{y}, \tilde{v}, \tilde{\xi})$ is a solution of (\mathcal{P}) . Moreover, we can ensure existence of Lagrange multipliers for the relaxed problem. For this purpose, we recall here the key result of [2] (there is a more general (abstract) result in the quoted paper):

Theorem 2.1. *Let $(y_\varepsilon, v_\varepsilon, \xi_\varepsilon)$ be a solution of $(\mathcal{P}_\varepsilon)$ and assume $-(f + w_\varepsilon)$ belongs to the L^∞ -interior of U_{ad} , where $w_\varepsilon = g'(y_\varepsilon)y_\varepsilon - g(y_\varepsilon)$ is the non linearity gap at the solution. Then Lagrange multipliers $(q_\varepsilon, r_\varepsilon) \in L^2(\Omega) \times \mathbb{R}_o^+$ exist, such that*

$$\forall y \in \tilde{K} \quad (p_\varepsilon + q_\varepsilon, [A + g'(y_\varepsilon)](y - y_\varepsilon)) + r_\varepsilon (\xi_\varepsilon, y - y_\varepsilon) \geq 0, \quad (2.10)$$

$$\forall v \in U_{ad} \quad (\alpha(v_\varepsilon - v_d) - q_\varepsilon, v - v_\varepsilon) \geq 0, \quad (2.11)$$

$$\forall \xi \in V_{ad} \quad (r_\varepsilon y_\varepsilon - q_\varepsilon, \xi - \xi_\varepsilon) \geq 0, \quad (2.12)$$

$$r_\varepsilon [(y_\varepsilon, \xi_\varepsilon) - \varepsilon] = 0, \quad (2.13)$$

where p_ε is given by

$$A^*p_\varepsilon + g'(y_\varepsilon)p_\varepsilon = y_\varepsilon - z_d \text{ on } \Omega, \quad p_\varepsilon \in H_o^1(\Omega), \quad (2.14)$$

and

$$\tilde{K} = \{y \in H^2(\Omega) \cap H_o^1(\Omega) \mid y \geq 0 \text{ in } \Omega\}.$$

Note that the adjoint equation (2.14) has a unique solution, since the adjoint operator A^* of A is also coercive and continuous and $g'(y_\varepsilon) \geq 0$.

From now, we focus on $(\mathcal{P}_\varepsilon)$ to get a numerical realization via different algorithms. There are two difficulties due to the different nonlinearities of the problem. The first one comes from the state equation which is semilinear, but we have good hope to solve it with SQP methods since the function g is non decreasing. The second one comes from the bilinear mixed state-control constraint

$(y, \xi) \leq \varepsilon$ which is not convex. Anyway, we have already dealt with this kind of constraint in [3]. The challenge is to take both nonlinearities into account.

From now we assume the existence of Lagrange multipliers, that satisfy the optimality system of Theorem 2.1. We may choose for example $U_{ad} = L^2(\Omega)$ or (see [2])

$$U_{ad} = [a, b] \quad \text{with } a + 3 + \varepsilon \leq b - \varepsilon, \quad \varepsilon > 0, \quad -b + \varepsilon \leq f \leq -a - 3 - \varepsilon \quad \text{and } g(x) = -\frac{1}{1+x^2}.$$

In this case $0 \leq w_\varepsilon \leq 3$ so that $-(f + w_\varepsilon) \in [a + \varepsilon, b - \varepsilon] \subset \text{Int}_{L^\infty}(U_{ad})$.

3. A SQP-Augmented Lagrangian Method

3.1. An Augmented Lagrangian Algorithm

It is easy to see that the multipliers given by Theorem 2.1 are associated to a saddle point of the linearized Lagrangian function of problem $(\mathcal{P}_\varepsilon)$. More precisely, let us define the Lagrangian function :

$$L_\varepsilon(y, v, \xi, q, r) = J(y, v) + (q, Ay + g(y) - f - v - \xi) + r[(y, \xi) - \varepsilon],$$

on $(H^2(\Omega) \cap H_o^1(\Omega)) \times L^2(\Omega) \times L^2(\Omega) \times L^2(\Omega) \times \mathbb{R}$, and the augmented Lagrangian function :

$$L_\varepsilon^c(y, v, \xi, q, r) = L_\varepsilon(y, v, \xi, q, r) + \frac{c}{2} \|Ay + g(y) - f - v - \xi\|^2 + \frac{c}{2} [(y, \xi) - \varepsilon]_+^2,$$

where $s_+ = \max(0, s)$ and $c > 0$.

Remark 3.1. We could replace the augmentation term $[(y, \xi) - \varepsilon]_+^2$ by any other augmentation function with the same properties. For example, one could set

$$\begin{aligned} L_\varepsilon^c(y, v, \xi, q, r) = & J(y, v) + (q, Ay + g(y) - f - v - \xi) + \max\left(-\frac{r}{c}, (y, \xi) - \varepsilon\right) \\ & + \frac{c}{2} \|Ay + g(y) - f - v - \xi\|^2 + \frac{c}{2} [\max\left(-\frac{r}{c}, (y, \xi) - \varepsilon\right)]^2, \end{aligned}$$

as in [11] or [14]. This does not change the forthcoming conclusions.

If $(y_\varepsilon, v_\varepsilon, \xi_\varepsilon)$ is a solution to problem $(\mathcal{P}_\varepsilon)$, then Theorem 2.1 yields that

$$\forall (q, r) \in L^2(\Omega) \times \mathbb{R}_0^+ \quad L_\varepsilon^c(y_\varepsilon, v_\varepsilon, \xi_\varepsilon, q, r) \leq L_\varepsilon^c(y_\varepsilon, v_\varepsilon, \xi_\varepsilon, q_\varepsilon, r_\varepsilon) = J(y_\varepsilon, v_\varepsilon) \quad (3.15)$$

$$\forall (y, v, \xi) \in \tilde{K} \times U_{ad} \times V_{ad} \quad \nabla_{y, v, \xi} L_\varepsilon^c(y_\varepsilon, v_\varepsilon, \xi_\varepsilon, q_\varepsilon, r_\varepsilon)(y - y_\varepsilon, v - v_\varepsilon, \xi - \xi_\varepsilon) \geq 0.$$

Of course, we cannot conclude that $(y_\varepsilon, v_\varepsilon, \xi_\varepsilon, q_\varepsilon, r_\varepsilon)$ is a saddle-point of L_ε^c since we have a lack of convexity. Anyway, if the bilinear constraint $(y, \xi) \leq \varepsilon$ were inactive, the problem would be locally convex and we could use the classical Uzawa algorithm to compute the solution. We use this remark and decide to use a variant of the Uzawa algorithm, even if we have no convexity property. In order to get a fast convergence behavior and an efficient implementation we decide to use a Gauss-Seidel type splitting as in [3, 6, 10].

This gives the following algorithm which convergence will be justified by fixed point arguments.

Algorithm \mathcal{A}

- Step 1. Initialization : Set $n = 0$, choose $q_o \in L^2(\Omega)$, $r_o \in \mathbb{R}_o^+$, $(v_{-1}, \xi_{-1}) \in U_{ad} \times V_{ad}$.
- Step 2. Compute

$$y_n = \arg \min \left\{ L_\varepsilon^c(y, v_{n-1}, \xi_{n-1}, q_n, r_n) \mid y \in \tilde{K} \right\} , \quad (3.16)$$

$$v_n = \arg \min \{ L_\varepsilon^c(y_n, v, \xi_{n-1}, q_n, r_n) \mid v \in U_{ad} \} , \quad (3.17)$$

$$\xi_n = \arg \min \{ L_\varepsilon^c(y_n, v_n, \xi, q_n, r_n) \mid \xi \in V_{ad} \} . \quad (3.18)$$

- Step 3. Compute

$$q_{n+1} = q_n + \rho_1 [Ay_n + g(y_n) - v_n - f - \xi_n] \quad \text{where } \rho_1 \geq \rho_o > 0 , \quad (3.19)$$

$$r_{n+1} = r_n + \rho_2 [(y_n, \xi_n) - \varepsilon]_+ \quad \text{where } \rho_2 \geq \rho_o > 0 . \quad (3.20)$$

Note that, if we do not care about constant terms

$$\begin{aligned} L_\varepsilon^c(y, v_{n-1}, \xi_{n-1}, q_n, r_n) &= \frac{1}{2} \|y - z_d\|^2 + (q_n, Ay + g(y)) + r_n (y, \xi_{n-1}) \\ &\quad + \frac{c}{2} [\|Ay + g(y) - v_{n-1} - f - \xi_{n-1}\|^2 + [(y, \xi_{n-1}) - \varepsilon]_+^2] , \end{aligned}$$

and

$$L_\varepsilon^c(y_n, v_n, \xi, q_n, r_n) = (r_n y_n - q_n, \xi) + \frac{c}{2} (\|Ay_n + g(y_n) - v_n - f - \xi\|^2 + [(y_n, \xi) - \varepsilon]_+^2) .$$

In addition, problem (??) of Step 2 is equivalent to

$$v_n = \pi_{U_{ad}}([v_d + q_n + c (Ay_n + g(y_n) - f - \xi_{n-1})]/[\alpha + c])$$

where $\pi_{U_{ad}}$ denotes the $L^2(\Omega)$ -projection on U_{ad} .

The above algorithm \mathcal{A} is based on the most “natural” penalization of the inequality constraint. We could replace this penalization by the one described in Remark 3.1.

3.2. A partial convergence result

Algorithm \mathcal{A} may be interpreted as a successive approximation method to compute the fixed-points of a function Φ defined below. We are able to prove that Φ is locally Lipschitz continuous but we cannot estimate precisely the Lipschitz constant. Our feeling is that an appropriate choice of parameters allows to make this constant strictly less than 1, so that Φ is contractive. To interpretate Algorithm \mathcal{A} , we define functions φ_i as follows :

(i) $\varphi_1 : L^2(\Omega) \times L^2(\Omega) \times L^2(\Omega) \times \mathbb{R}_o^+ \rightarrow H^2(\Omega) \cap H_o^1(\Omega) :$

$$\varphi_1(v, \xi, q, r) = y^* = \text{Arg} \min \left\{ L_\varepsilon^c(y, v, \xi, q, r) \mid y \in \tilde{K} \right\} . \quad (3.21)$$

(ii) $\varphi_2 : H^2(\Omega) \cap H_o^1(\Omega) \times L^2(\Omega) \times L^2(\Omega) \rightarrow L^2(\Omega) :$

$$\varphi_2(y, q, \xi) = v^* = \pi_{U_{ad}} \left(\frac{v_d + q + c(Ay + g(y) - f - \xi)}{\alpha + c} \right) . \quad (3.22)$$

(iii) $\varphi_3 : (H^2(\Omega) \cap H_o^1(\Omega)) \times L^2(\Omega) \times L^2(\Omega) \times \mathbb{R}_o^+ \rightarrow L^2(\Omega) :$

$$\varphi_3(y, v, q, r) = \xi^* = \text{Arg} \min \{ L_\varepsilon^c(y, v, \xi, q, r) \mid \xi \in V_{ad} \} . \quad (3.23)$$

(iv) $\varphi_4 : (H^2(\Omega) \cap H_o^1(\Omega)) \times L^2(\Omega) \times L^2(\Omega) \times L^2(\Omega) \times \mathbb{R}_o^+ \rightarrow L^2(\Omega) \times \mathbb{R}_o^+ :$

$$\varphi_4(y, v, \xi, q, r) = (q^*, r^*) = (q + \rho_1[Ay + g(y) - v - f - \xi], r + \rho_2 [(y, \xi) - \varepsilon]_+) .$$

At last, let us define $\Phi : L^2(\Omega) \times L^2(\Omega) \times L^2(\Omega) \times \mathbb{R}_o^+ \rightarrow L^2(\Omega) \times L^2(\Omega) \times L^2(\Omega) \times \mathbb{R}_o^+ :$

$$\Phi(v, \xi, q, r) = (\bar{v}, \bar{\xi}, \bar{q}, \bar{r}) ,$$

with

$$\bar{y} = \varphi_1(v, \xi, q, r) ,$$

$$\bar{v} = \varphi_2(\bar{y}, q, \xi) = \varphi_2(\varphi_1(v, \xi, q, r), q, \xi) ,$$

$$\bar{\xi} = \varphi_3(\bar{y}, \bar{v}, q, r) = \varphi_3(\varphi_1(v, \xi, q, r), \varphi_2(\varphi_1(v, \xi, q, r), q, \xi), q, r) ,$$

$$(\bar{q}, \bar{r}) = \varphi_4(\bar{y}, \bar{v}, \bar{\xi}, q, r)$$

$$= \varphi_4(\varphi_1(v, \xi, q, r), \varphi_2(\varphi_1(v, \xi, q, r), q, \xi), \varphi_3(\varphi_1(v, \xi, q, r), \varphi_2(\varphi_1(v, \xi, q, r), q, \xi), q, r), q, r) .$$

All product spaces are endowed with the ℓ^1 product norm. So Algorithm \mathcal{A} turns to be exactly the successive approximation method applied to Φ , to solve

$$\Phi(v, \xi, q, r) = (v, \xi, q, r) . \quad (3.24)$$

To prove the convergence we should prove first that Φ is contractive. Then, we have to show that the solution $(\bar{v}, \bar{\xi}, \bar{q}, \bar{r})$ of (3.24) satisfies the optimality system of Theorem 2.1 with $\tilde{y} = \varphi_1(\bar{v}, \bar{\xi}, \bar{q}, \bar{r})$.

Theorem 3.2. *The function Φ defined above is locally Lipschitz continuous.*

We omit the proof which is quite long and technical (but easy) and can be found in [4]. In particular, it is almost impossible (in the general case) to obtain a precise estimate of the Lipschitz-constant. We only know that the constant depends on the neighborhood of the initial point (v_o, ξ_o, q_o, r_o) , the augmentation parameter c and the function g . We have to prove that this constant is strictly less than 1 to apply some fixed point theorem. Anyway, our feeling is that it is possible to let the constant strictly less than 1 if the different parameters of Algorithm, namely ρ_1, ρ_2, c and the initial point (v_o, ξ_o, q_o, r_o) are well chosen. Of course, the convergence will be local.

It remains to prove that the fixed point of Φ (whenever it exists) is a stationary point, i.e a solution of the optimality system of Theorem 2.1.

Theorem 3.3. *Every solution $(\bar{v}, \bar{\xi}, \bar{q}, \bar{r})$ of (3.24) satisfies the relations (2.10)-(2.12) of Theorem 2.1.*

Proof. Let be $(\bar{v}, \bar{\xi}, \bar{q}, \bar{r})$ a fixed-point of Φ and set $\tilde{y} = \varphi_1(\bar{v}, \bar{\xi}, \bar{q}, \bar{r})$. The definition of Φ yields

$$\bar{v} = \varphi_2(\tilde{y}, \bar{q}, \bar{\xi}) , \quad \bar{\xi} = \varphi_3(\tilde{y}, \bar{v}, \bar{q}, \bar{r}) , \quad (3.25)$$

$$(\bar{q}, \bar{r}) = \varphi_4(\tilde{y}, \bar{v}, \bar{\xi}, \bar{q}, \bar{r}) . \quad (3.26)$$

Relation (3.26) gives :

$$\bar{q} = \bar{q} + \rho_1(A\tilde{y} + g(\tilde{y}) - \bar{v} - f - \bar{\xi}) \quad \text{and} \quad \bar{r} = \bar{r} + \rho_2[(\tilde{y}, \bar{\xi}) - \varepsilon]_+ ,$$

so that

$$A\tilde{y} + g(\tilde{y}) - \tilde{v} - f - \tilde{\xi} = 0 \quad \text{and} \quad (\tilde{y}, \tilde{\xi}) \leq \varepsilon, \quad (3.27)$$

since $\min\{\rho_1, \rho_2\} \geq \rho_o > 0$. As $\tilde{y} \in \tilde{K}$, $\tilde{v} \in U_{ad}$ and $\tilde{\xi} \in V_{ad}$, this means that $(\tilde{y}, \tilde{v}, \tilde{\xi})$ is feasible for the problem $(\mathcal{P}_\varepsilon)$.

Now we write successively the optimality systems related to the definitions of φ_1 , φ_2 and φ_3 . From the definition of φ_1 we get for all $y \in \tilde{K}$

$$\begin{aligned} & (\tilde{y} - z_d, y - \tilde{y}) + (\tilde{q}, [A + g'(\tilde{y})](y - \tilde{y})) + \tilde{r} (\tilde{\xi}, y - \tilde{y}) + \\ & c \left(A\tilde{y} + g(\tilde{y}) - \tilde{v} - \tilde{\xi} - f, [A + g'(\tilde{y})](y - \tilde{y}) \right) + c[(\tilde{y}, \tilde{\xi}) - \varepsilon]_+ (\tilde{\xi}, y - \tilde{\xi}) \geq 0, \end{aligned}$$

and with (3.27)

$$(\tilde{y} - z_d, y - \tilde{y}) + (\tilde{q}, [A + g'(\tilde{y})](y - \tilde{y})) + \tilde{r} (\tilde{\xi}, y - \tilde{y}) \geq 0.$$

This is exactly relation (2.10) with $(\tilde{y}, \tilde{\xi}, \tilde{q}, \tilde{r})$ instead of $(y_\varepsilon, \xi_\varepsilon, q_\varepsilon, r_\varepsilon)$.

Similarly, one can show that relations (2.11) and (2.12) are satisfied for $(\tilde{y}, \tilde{v}, \tilde{\xi}, \tilde{q}, \tilde{r})$. \square

3.3. Implementation : an “equivalent” algorithm

We detail here how we may solve subproblems (3.16) and (3.18). We first focus on (3.16) that may be written as follows

$$\min \left\{ \frac{1}{2} \|y - z_d\|^2 + (\bar{q}, Ay + g(y)) + \bar{r} (y, \bar{\xi}) + \frac{c}{2} [\|Ay + g(y) - \bar{w}\|^2 + [(y, \bar{\xi}) - \varepsilon]_+^2] \mid y \in \tilde{K} \right\},$$

where \bar{q} , \bar{r} , $\bar{\xi}$ and \bar{w} are given. This problem is not immediately amenable to SQP-methods due to the lack of twice (continuous) differentiability of the objective functional. In fact, note that the $[\cdot]_+$ term is not \mathcal{C}^2 . However, noticing that the penalization, i.e. the term under brackets in (3.16) together with $c > 0$, is exact if c is large enough ([9]) we decide to minimize the following cost functional :

$$\frac{1}{2} \|y - z_d\|^2 + (\bar{q}, Ay + g(y)) + \bar{r} (y, \bar{\xi}) + \frac{c}{2} [\|Ay + g(y) - \bar{w}\|^2]$$

for c sufficiently large, instead of the original one. Therefore, we rather solve

$$(P_y) \quad \min \left\{ \frac{1}{2} \|y - z_d\|^2 + \bar{r} (y, \bar{\xi}) + (\bar{q}, Ay + g(y)) + \frac{c}{2} [\|Ay + g(y) - \bar{w}\|^2] \mid y \in \tilde{K} \quad (y, \bar{\xi}) \leq \varepsilon \right\},$$

than (3.16). In this form, (P_y) can be solved by SQP-techniques. Problem (3.18) will be solved similarly: we remove the non differentiable term in the cost functional to obtain a linear-quadratic problem

$$(P_\xi) \quad \min \left\{ (\bar{r}\bar{y} - \bar{q}, \xi) + \frac{c}{2} [\|A\bar{y} + g(\bar{y}) - \bar{v} - f - \xi\|^2] \mid \xi \in V_{ad}, (\bar{y}, \bar{\xi}) \leq \varepsilon \right\},$$

We note that the update of multiplier r_n has to be checked carefully: we may decide to keep (3.20). This means that r_n is constant equal to r_o (fixed during the initialization process). Alternatively, we may update r_n by utilizing the Lagrange multiplier associated to the constraint $(y_n, \xi) \leq \varepsilon$ in (P_ξ) . Let \tilde{r}_n denote the corresponding multiplier. Then Algorithm \mathcal{A} becomes:

Algorithm \mathcal{A}^*

Step 1. Initialization : Set $n = 0$, choose $q_o \in L^2(\Omega)$, $r_o \in \mathbb{R}_o^+$, $(v_{-1}, \xi_{-1}) \in U_{ad} \times V_{ad}$.

Step 2. Compute

- (P_y) to get

$$y_n = \arg \min \left\{ \frac{1}{2} \|y - z_d\|^2 + r_n(y, \xi_{n-1}) + (q_n, Ay + g(y)) + \frac{c}{2} \|Ay + g(y) - v_{n-1} - f - \xi_{n-1}\|^2 \right. \\ \left. \mid y \in \tilde{K} \text{ and } (y, \xi_{n-1}) \leq \varepsilon \right\} .$$

- $v_n = \pi_{U_{ad}}([q_n + c(Ay_n + g(y_n)) - f - \xi_{n-1}]/[\alpha + c])$.
- (P_ξ) to get

$$\xi_n = \arg \min \left\{ (r_n y_n - q_n, \xi) + \frac{c}{2} \|Ay_n + g(y_n) - v_n - f - \xi\|^2 \mid \xi \in V_{ad}, (y_n, \xi) \leq \varepsilon \right\} ,$$

with \tilde{r}_n the multiplier associated with $(y_n, \xi) \leq \varepsilon$.

Step 3. Set $r_n = \tilde{r}_n$ and compute

$$q_{n+1} = q_n + \rho [Ay_n + g(y_n) - v_n - f - \xi_n] \text{ where } \rho \geq \rho_o > 0 ,$$

We apply a classical SQP method to solve (P_y) : the linearized, associated sub-problem has a quadratic cost functional and the same constraints as (P_y) (that were already linear). Using a slackness variable the discretized subproblem can be written formally as

$$(P^\ell) \begin{cases} \min \frac{1}{2} z^t Q z + b^t z \\ a^t z = \varepsilon , \\ z \geq 0 , \end{cases}$$

where $Q = \begin{pmatrix} H & 0 \\ 0 & 0 \end{pmatrix}$ is a $N \times N$ matrix such that H is a positive $(N - 1) \times (N - 1)$ matrix, $b, a \in \mathbb{R}^N$ and $\varepsilon > 0$.

We tried many methods to solve this subproblem: interior-point algorithms ([8] for example), projected Newton method and active set method as in [12, 5]. We decided to use an active set method. We do not report here on the two others but their performance was inferior with respect to the active set strategy. Since (P_ξ) is a linear-quadratic problem there is no necessity for an SQP step.

4. Numerical Experiments

In this section, we report on two 2D-examples. The discretization process was based on finite difference schemes with a grid size $N \times N$. Of course, we have performed many tests, especially for the linear case ($g \equiv 0$) where the results were completely consistent with the ones of [13]. In this paper we do not consider control constraints though tests have been done : the method works well

and we shall report on these examples in a forthcoming paper. The stopping criterion has been set to

$$\sigma_n = \max\{\|y_n - y_{n-1}\|_\infty, \|v_n - v_{n-1}\|_2, \|\xi_n - \xi_{n-1}\|_2, \|Ay_n + g(y_n) - v_n - f - \xi_n\|_2\} \leq tol ,$$

where tol is a prescribed tolerance. We have tried different updates for the multiplier r_n

- Update (1): first, we decide to set $r_n \equiv r_o$ during the whole iteration process. We have tested large and small values for r_o (including $r_o = 0$). Note that the term $r_n(y, \xi_{n-1})$ acts as a penalization term in the cost functional of problem (P_y) (and similarly for (P_ξ)): if r_o is large then we may obtain $(y, \xi_{n-1}) = 0$. This will be observed numerically.
- Update (2): r_n is the multiplier associated to the constraint $(y_n, \xi) \leq \varepsilon$ obtained when computing ξ_n , the solution to (P_ξ) .

Data and parameters were set to :

$$\Omega =]0, 1[\times]0, 1[, A = -\Delta , tol = 10^{-3}, \varepsilon = 10^{-3}, c = \alpha, \rho = \alpha, y_o = \psi \text{ (initialization)} .$$

The choice of c is based on different numerical tests that showed that the choice was the “best” (on can refer to Table 1. below). The algorithm is not sensitive to the choice of the initialization point. The number of SQP iterations has been limited to 10: we never observed a situation where this bound was reached.

4.1. Examples

1. Example 1 .

$$z_d = 1 , v_d = 0, \alpha = 0.1 , U_{ad} = L^2(\Omega) , g(y) = y^3 .$$

$$f(x_1, x_2) = \begin{cases} 200 [2 x_1 (x_1 - 0.5)^2 - x_2(1 - x_2)(6x_1 - 2)] & \text{if } x_1 \leq 0.5 , \\ 200 (0.5 - x_1) & \text{else.} \end{cases}$$

$$\psi(x_1, x_2) = \begin{cases} 200 [x_1 x_2 (x_1 - 0.5)^2(1 - x_2)] & \text{if } x_1 \leq 0.5 , \\ 200 [(x_1 - 1) x_2 (x_1 - 0.5)^2(1 - x_2)] & \text{else.} \end{cases}$$

Obstacle

Source term

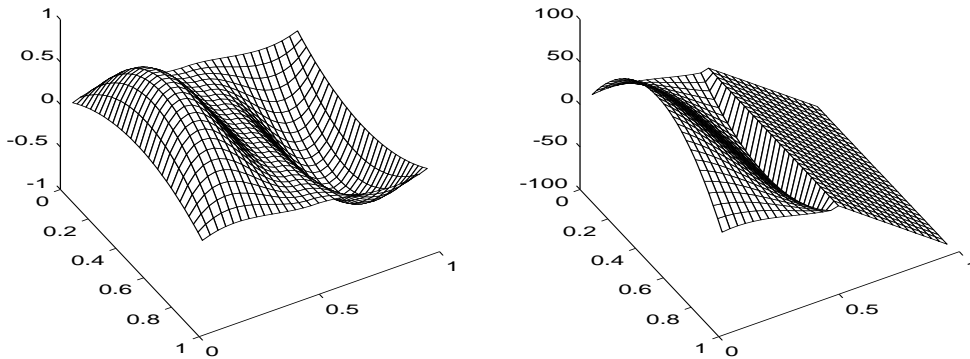


Figure 1 : Data

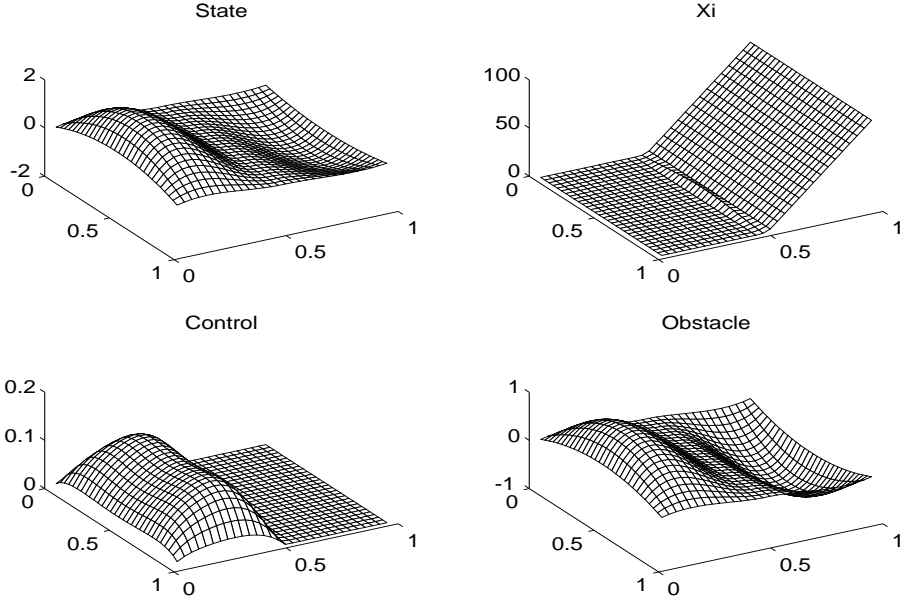


Figure 2 : Optimal Solution

2. Example 2 .

$$v_d = 0, \alpha = 0.01, U_{ad} = L^2(\Omega), g(y) = y^3.$$

$$f(x_1, x_2) = \begin{cases} 200 [2x_1(x_1 - 0.5)^2 - x_2(1 - x_2)(6x_1 - 2)] & \text{if } x_1 \leq 0.5, \\ 200(0.5 - x_1) & \text{else.} \end{cases}, \psi = -\Delta^{-1}(f), \psi \in H_o^1(\Omega),$$

$$z_d(x_1, x_2) = \begin{cases} 200 [x_1 x_2 (x_1 - 0.5)^2 (1 - x_2)] & \text{if } x_1 \leq 0.5, \\ 200 [(x_1 - 1) x_2 (x_1 - 0.5)^2 (1 - x_2)] & \text{else.} \end{cases}$$

Numerical tests have been performed on a DEC-alpha station, using MATLAB software.

4.2. Numerical tests

4.2.1. Choice of the parameter c

We have already mentioned that a good choice for c was α . Table 1. presents the behavior of the algorithm for different values of c for Example 1. The grid size was set to $N = 20$. We recall that $\alpha = 10^{-1}$.

c	Update (1) with $r_o = 0$			Update (2)		
	# it. (1st level)	Total # it. (with SQP)	σ_n (last iterate)	# it. (1st level)	Total # it. (with SQP)	σ_n (last iterate)
10	Slow convergence STOP at it. 100	201	3.52	Slow convergence STOP at it. 100	199	3.53
1	Slow convergence STOP at it. 100	198	$4.9 \cdot 10^{-1}$	Slow convergence STOP at it. 100	205	$5.8 \cdot 10^{-1}$
$10^{-1} (= \alpha)$	34	61	$8 \cdot 10^{-4}$	34	61	$9 \cdot 10^{-4}$
10^{-2}	61	116	$8 \cdot 10^{-5}$	51	96	$2 \cdot 10^{-4}$

Table 1: Sensitivity with respect to the augmentation parameter c - Example 1 - $N = 20$

Here the first column (# it.) denotes the number of global iterations (first level of the loop) and the second one the total number of iterations (including iterations during the SQP loop).

4.2.2. Update of multiplier r_n

We have tested different updates for the multiplier r_n . As mentioned before, if r_n is constant and “large” the constraint $(y, \xi) = 0$ could be satisfied, but the convergence rate is worse. It seems that there is a conflict between the state-constraint and the constraint $(y, \xi) = 0$ during the resolution of (P_y) . Example 1. shows that there may be no convergence (cyclic scattering). Therefore, r_n must be “small” (with respect to α): 0 for example. We observe also that updating the multiplier with update (2), gives a similar convergence rate in the case of Example 1.

r_n	# it. (first level)	Total # it.(with SQP)	$(y - \psi, \xi)$
0	34	61	10^{-3}
5	35	62	$6.4 \cdot 10^{-5}$
10	STOP at it. 100	230	0
Update (2)	34	61	10^{-3}

Table 2 : Sensitivity with respect to the update of r_n - Example 1 - N=20

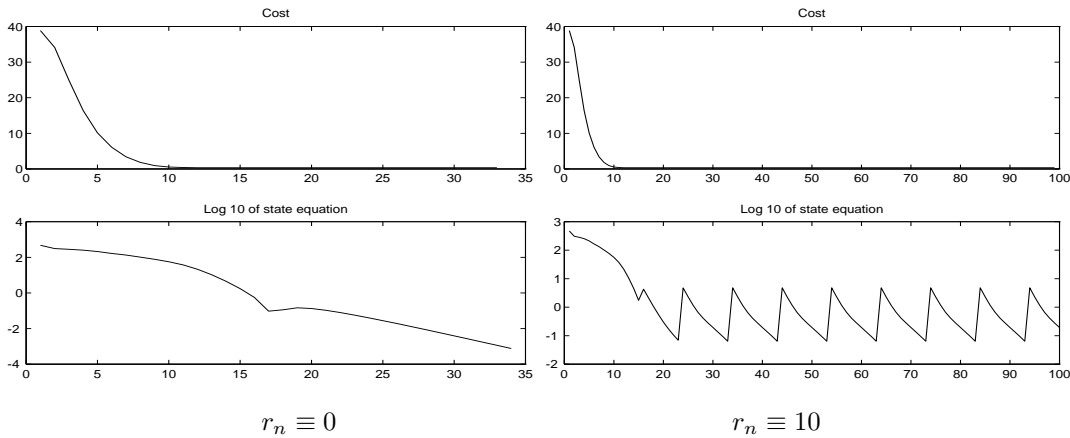


Figure 3 : Convergence rate for update (1) - Example 1 - N=20

However, this phenomenon is not stable : we observe with Example 2. that the choice of update (2) may lead to divergence.

r_n	# it.(first level)	Total # it.(with SQP)	$(y - \psi, \xi)$
0	39	59	10^{-3}
Update 2.	STOP at it. 120 (Divergence)	167	

Table 3: Sensitivity with respect to the update of r_n - Example 2 - N=25

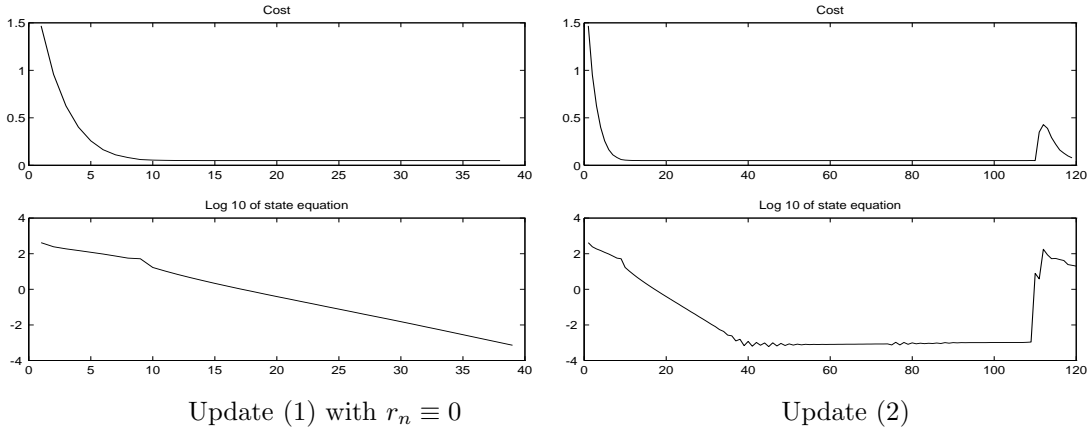


Figure 4 : Convergence rate for update (1) and (2) - Example 2 - $N=25$

4.2.3. Mesh dependence

At last we verify that there is no mesh independence (see Table 4 below):

Grid size	# it.(first level)	Total # it. (with SQP)
10	28	17
15	36	56
20	34	47
25	47	79
30	57	85
35	60	101
40	89	125
45	76	119
50	81	120
55	90	140
60	98	145

Table 4: Mesh dependence for $r_n \equiv 0$ - Example 1

5. Conclusions

This algorithm is performant since it always provides solutions without a fine tuning of different parameters. Most of time, we observe exponential decay for the state equation, but scattering is possible (especially when the update of the multiplier r_n is inappropriate). Generally, the cost functional is decreasing but we are not able to prove it for the moment. The “bad points” of this method are the following :

- There is no mesh independence
- The convergence is slow : the resolution of the quadratic subproblem (P^ℓ) is the most expensive step. We investigate multigrid methods to improve the convergence rate.

We have just presented this method without a complete numerical checking. This will be done in a forthcoming paper : most of numerical aspects will be reviewed and a comparison with other methods (especially finite dimensional methods for complementarity problems) will be performed.

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UMR-CNRS 6628, Université d’Orléans,

U.F.R. Sciences,

B.P. 6759,

F-45067 Orléans Cedex 2, France

E-mail address: {Maitine.Bergounioux, Mounir.Haddou}@labomath.univ-orleans.fr