On the paper "Augmented Lagrangian algorithms for solving the continuous nonlinear resource allocation problem"

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Abstract

In the paper *[Torrealba, E.M.R. et al. Augmented Lagrangian algorithms for solving the continuous nonlinear resource allocation problem. EJOR, 299(1) 46–59, 2021]* an augmented Lagrangian algorithm was proposed for resource allocation problems with the intriguing characteristic that instead of solving the box-constrained augmented Lagrangian subproblem, they propose projecting the solution of the unconstrained subproblem onto such box. A global convergence result for the quadratic case was provided, however, this is somewhat counterintuitive, as in usual augmented Lagrangian theory, this strategy can fail in solving the augmented Lagrangian subproblems. In this note we investigate further this algorithm and we show that the proposed method may indeed fail when the Hessian of the quadratic is not a multiple of the identity. In the paper, it is not clear enough that two different projections are being used: one for obtaining their convergence results and other in their implementation. However, despite the lack of theoretical convergence, their strategy works remarkably well in some classes of problems; thus, we propose a hybrid method which uses their idea as a starting point heuristics, switching to a standard augmented Lagrangian method under certain conditions. Our contribution consists in presenting an efficient way of determining when the heuristics is failing to improve the KKT residual of the problem, suggesting that the heuristic procedure should be abandoned. Numerical results are provided showing that this strategy is successful in accelerating the standard method.

Keywords: Nonlinear programming, Resource allocation problem, Augmented Lagrangian method.

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1 Introduction

The knapsack problem is the minimization problem of

$$\begin{array}{ll} \text{Minimize} & \sum x^T y, \\ \text{s.t.} & b^T x = c, \\ & x \in \{0,1\}, \end{array} \tag{1}$$

originally it was formulated as the problem of best fitting several items on a knapsack while attaining its maximum capacity, hence the name. Throughout the years this problem has been well studied with applications in several fields such as economics, engineering and computer theory. It also appears as subproblems in several applications, such as in equilibration procedures for traffic flows (see [Lotito (2006)]) and so on. The knapsack problem has been extended to broader classes of functions, including separable or just convex functions, as seen in [Hochbaum (1995)]; and substituting the integer constraints for other discrete sets, or continuous bounded sets such as boxes. Whenever the integer condition is substituted by a continuous box, the problem is referred as "continuous knapsack problem". For a survey on the matter see [Patriksson (2008)].

There are several methods tailored to this class of problems, and due to its particular structure, a solution can be found very quickly in comparison to using a general purpose algorithm. Continuous knapsack problems may be classified in several different subclasses, with different algorithms and applications, as exploited in [Bretthauer and Shetty (2002)]. In this paper we address the continuous quadratic resource allocation problem.

When the problem is separable, one may consider the pegging method, see for instance [Bretthauer and Shetty (2002)], branch and bound methods as in [Li and Sun (2006)], or Newton type methods such as [Cominetti et al. (2014)]. Lagrange multiplier methods for non-separable problems can be found in [Bretthauer and Shetty (2002)], or in [Patriksson and Strömberg (2015)]. A complete open source library for the general case is available in [Frangioni and Gorgone (2013)]. In [Torrealba et al. (2021)] an augmented Lagrangian method for non-separable problems was proposed. Namely, they considered the problem

$$\begin{array}{ll} \text{Minimize} & f(x), \\ \text{s.t.} & b^T x = c, \\ & \ell \le x \le u, \end{array} \tag{2}$$

where $f : \mathbb{R}^n \to \mathbb{R}$ is a continuously differentiable convex function and b, ℓ, and u are vectors in $\mathbb{R}^n$ with $c \in \mathbb{R}$. Considering the Powell-Hestenes-Rockafellar augmented Lagrangian function $L(x, \lambda, r) = f(x) + \lambda(b^T x - c) + \frac{r}{2}(b^T x - c)^2$ corresponding to penalization of the equality constraints, a standard augmented Lagrangian method would define a sequence of penalty parameters $\{r^k\}$ and a sequence of approximate Lagrange multipliers $\{\lambda^k\}$ in order to define a sequence of approximate solutions $\{x^k\}$ by means of approximately solving the sequence of subproblems

$$\begin{array}{ll} \text{Minimize} & L(x, \lambda^k, r^k), \\ \text{s.t.} & \ell \le x \le u. \end{array} \tag{3}$$

In [Torrealba et al. (2021)], the authors propose defining the sequence $\{x^k\}$ alternatively by

$$x^k = \Pi_{[\ell,u]}(\arg\min_{x\in\mathbb{R}^n} L(x, \lambda^k, r^k)), \tag{4}$$

however, the projection operator $\Pi_{[\ell,u]}(\cdot)$ onto the box $[\ell, u]$ is used in the paper somewhat loosely, as in their experiments they considered it to mean the Euclidean projection, whereas in their convergence results, more specifically on the quadratic case, they considered the functions

$$f(x) := \frac{1}{2}x^T Px - a^T x, \tag{5}$$

with $a \in \mathbb{R}^n$ and P a positive definite matrix, and the projection is taken with respect to the so-called P-norm, which is defined by $\|u\|_P := \sqrt{u^T Pu}$ for all $u \in \mathbb{R}^n$. When considering the Euclidean projection, the authors were able to present a somewhat simple formula for computing (4), which makes the strategy appealing, whereas computing the projection with respect to the P-norm may be as hard as solving the standard subproblem (3). Unfortunately, when x^k is computed with the Euclidean projection, this strategy may fail, as shown in the next example.

Example 1.1 *Consider the problem*

$$\begin{array}{ll} \textit{Minimize} & f(x, y, z) := x^2 - 2xy + 2y^2 + z^2, \\ \textit{s.t.} & z = 0, \\ & (1, 0, -1) \leq (x, y, z) \leq (5, 1, 1). \end{array} \tag{6}$$

The augmented Lagrangian function for this problem is given by

$$L(x, y, z, \lambda, r) := x^2 - 2xy + 2y^2 + z^2 + \lambda z + \frac{r}{2}z^2,$$

whose gradient with respect to (x, y, z) *is given by*

$$\nabla L\,(x, y, z, \lambda, r) = \begin{bmatrix} 2x - 2y \\ -2x + 4y \\ (2 + r)z + \lambda \end{bmatrix}.$$

In order to compute (4)*, one must first solve the system* $\nabla L(x, y, z, \lambda, r) = 0$*, which clearly gives* $x = y = 0$ *and* $z = -\frac{\lambda}{2+r}$*. Thus, when using the Euclidean projection in* (4)*, one arrives at the point* $(1, 0, \max\{-1, \min\{1, z\}\})^T$*. Assuming that the algorithm converges to a feasible point, it can only converge to* $(1, 0, 0)^T$*, which is not a solution of the problem (notice that* $f(1, \frac{1}{2}, 0) < f(1, 0, 0)$*, with* $(1, \frac{1}{2}, 0)$ *being the actual solution).*

In fact, the direction $x^{k+1} - x^k$ found by the algorithm in [Torrealba et al. (2021)] using the Euclidean projection may not even be a descent direction, as is shown in the extreme example below, where we start at the solution of the problem (minimizer) and converge to a maximizer instead.

Example 1.2 *Consider the problem*

$$\begin{array}{ll} \textit{Minimize} & f(x,y) := 45x^2/2 - 20xy + 5y^2 + 30x - 20y, \\ \textit{s.t.} & y = 1, \\ & (0,0) \le (x,y) \le (1,1). \end{array}$$

One can check that the minimizer for this problem is $(0,1)^T$ while $(1,1)^T$ is the maximizer. Starting the algorithm at the minimizer with $\lambda = 0$ and $r = 1$, and iterating as (4) with the Euclidean projection the method converges to the maximizer point $(1,1)^T$ satisfying both stopping criteria in [Torrealba et al. (2021)] already in the first iteration.

It is important to emphasize that the convergence theory for the quadratic case in Section 2 of [Torrealba et al. (2021)] is not wrong, it is in fact correct if one uses (4) with projection with respect to the P-norm, however it is not clear how one would be able to compute this projection efficiently. Examples 1.1 and 1.2 illustrate that defining an augmented Lagrangian iteration with the iterate x^k given by (4) may not work in general using the Euclidean projection. In the examples presented in Section 4.3 of [Torrealba et al. (2021)] they considered quadratic functions (5) with P being a multiple of the identity matrix, which implies that the Euclidean projection coincides with the projection with respect to the P-norm. Thus those numerical results are consistent with their theory. However, for the problems in Section 4.2 of [Torrealba et al. (2021)], a full matrix P is taken from the literature, which does not imply equality of the aforementioned projections. Despite that, surprisingly, numerical convergence to a solution is still achieved. In fact, even though the augmented Lagrangian subproblems are not being solved, the method somehow is able to converge to a solution. We show a particular example of this behavior in the next example:

Example 1.3 *Consider the problem*

$$\begin{array}{cc} \min & \frac{1}{2}x^T P x - a^T x, \\ s.t & x + y = 0, \\ & (0,-1) \le (x,y) \le (5,1), \end{array}$$

with $P = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}$, $a = (4,-4)^T$.

Applying the algorithm from [Torrealba et al. (2021)] using the Euclidean projection to this problem with $x^0 = (0,1)^T$ and $\lambda = 1$, the sequence $\{x^k\}$ generated converges to the actual solution $(1,-1)^T$, yet $\|P_{[\ell,u]}(x^k - \nabla L(x^k, \lambda^k, r^k))\| = 1$ for every k, which means that the augmented Lagrangian subproblems (3) are not being solved. This behavior is possible due to the fact that the generated sequence of approximate Lagrange multipliers $\{\lambda^k\}$ does not approximate the correct value $\lambda = 2$. The behavior is the same even if one starts the algorithm at the true Lagrange multiplier at the solution.

In the next section we propose a hybrid algorithm which uses the algorithm from [Torrealba et al. (2021)] unless it starts to fail in solving the original problem. That is, we compute x^k by (4) using the Euclidean projection, benefiting from the efficiency of the proposal in [Torrealba et al. (2021)], and then we monitor the progress in solving the original problem in terms of its KKT residual. This can be done by finding suitable approximate Lagrange multipliers associated with x^k by means of a least squares procedure, which we show that has a closed form solution. Once it is detected that an iterate x^k fails in reducing the KKT residual, the method may switch to any other strategy with guaranteed convergence. We show that this hybrid strategy when combined with a standard augmented Lagrangian or with the multiplier search method as in [Bretthauer and Shetty (2002)] outperforms the corresponding standard method and is more robust than the algorithm introduced in [Torrealba et al. (2021)].

2 A Hybrid General Framework

As previously mentioned, one should compute an iterate x^k by means of (4) using the projection with respect to the P-norm in order for the algorithm in [Torrealba et al. (2021)] to enjoy global convergence. However, in most cases, computing this projection is intractable. It turns out that by using the Euclidean projection instead, this computation is straightforward. Thus, we will investigate the use of the Euclidean projection in (4) as an heuristic for speeding up the standard augmented Lagrangian method.

Since we do not expect x^k as computed in (4) to solve the corresponding subproblem of the augmented Lagrangian (3), even when the method performs well, we must devise a way of checking whether the iterates computed in this way are successful or not. If not, one should abandon the heuristic and solve (3) with a standard method. We do so by measuring the progress of $x := x^k$ in satisfying the Karush-Kuhn-Tucker (KKT) conditions of the original problem (2), when the objective function is the quadratic (5), which states that x is feasible for (2) and there must exist Lagrange multipliers $\lambda \in \mathbb{R}$ and $\mu \in \mathbb{R}^n$ such that

$$Px - a + \lambda b + \mu = 0, \tag{7}$$

$$\mu_i \leq 0 \text{ if } x_i = \ell_i,\ \mu_i \geq 0 \text{ if } x_i = u_i, \text{ and } \mu_i = 0 \text{ otherwise, } i = 1, \cdots, n. \tag{8}$$

Here, λ is the Lagrange multiplier with respect to the equality constraint while μ is the Lagrange multiplier with respect to the box constraints $\ell \leq x \leq u$. Since feasibility is already being controlled by the augmented Lagrangian, we shall monitor the KKT-residual of an iterate x^k by means of how well equations (7) and (8) are being satisfied at $x := x^k$ for a suitable choice of λ and μ.

As the multiplier generated by the algorithm presented in [Torrealba et al. (2021)] may not converge to the correct multiplier, we developed an efficient way to check the KKT residual in x^k. More precisely, for $x := x^k$, we shall compute a least squares solution (λ, μ) of (7)-(8) and measure the corresponding residual. The sign constraints on μ are ignored in computing the least squares solution, which is then projected onto the appropriate orthant, while for inactive constraints the multiplier is forced to be zero.

In order to do so, we deal first with (8) by considering the set $I \subseteq \{1, \cdots, n\}$ of active constraints at x^k, that is, the set of indexes i such that $(x^k)_i = \ell_i$ or $(x^k)_i = u_i$ and we define $\mu_i = 0$ for all $i \notin I$. For simplicity of notation, let us assume that $I = \{1, \dots, q\} \subseteq \{1, \dots, n\}$. Denoting $v = a - Px^k$, we may write (7) as the linear system

$$\begin{bmatrix} I_q & \overline{b} \\ 0 & \tilde{b} \end{bmatrix} \begin{bmatrix} \overline{\mu} \\ \lambda \end{bmatrix} = \begin{bmatrix} \overline{v} \\ \tilde{v} \end{bmatrix}, \tag{9}$$

where I_q is the identity matrix of size $q \times q$ and we consider the partition of the vectors $b^T = [\overline{b}^T \quad \tilde{b}^T]$ and $v^T = [\overline{v}^T \quad \tilde{v}^T]$ in their first q components and the remaining ones. The vector $\overline{\mu}$ represents the first q components of μ, being the remaining ones equal to zero.

Since (9) is not expected to have a solution, we compute its least squares solution, whose corresponding normal equation reads as follows:

$$\begin{bmatrix} I_q & \overline{b} \\ \overline{b}^T & \|b\|^2 \end{bmatrix} \begin{bmatrix} \overline{\mu} \\ \lambda \end{bmatrix} = \begin{bmatrix} \overline{v} \\ b^T v \end{bmatrix}. \tag{10}$$

We can now solve the system by performing an elementary row operation on (10), arriving at the equivalent system

$$\begin{bmatrix} I & \overline{b} \\ 0^T & \|b\|^2 - \|\overline{b}\|^2 \end{bmatrix} \begin{bmatrix} \overline{\mu} \\ \lambda \end{bmatrix} = \begin{bmatrix} \overline{v} \\ b^T v - \overline{b}^T \overline{v} \end{bmatrix}, \tag{11}$$

which gives

$$\lambda = \frac{\tilde{b}^T \tilde{v}}{\|b\|^2 - \|\overline{b}\|^2} \tag{12}$$

and

$$\overline{\mu} = \overline{v} - \lambda \overline{b}. \tag{13}$$

In order to address the sign constraint in (8), we project $\overline{\mu}$ onto the appropriate orthant. That is, we redefine $\overline{\mu}$ as $\overline{\mu}_i := \max\{0, \overline{\mu}_i\}$ when $(x^k)_i = u_i$, and $\overline{\mu}_i := \min\{0, \overline{\mu}_i\}$ when $(x^k)_i = \ell_i$ for all $i \in I$. Notice that when x^k is a minimizer of (2) with a unique Lagrange multiplier associated, this procedure is capable of computing the multiplier with the correct sign.

Then, after computing λ and μ in this way, we define the KKT-residual ϵ^{k+1} at each iterate x^k by

$$\varepsilon^{k+1} := \|Px^k - a + \lambda b + \mu\|. \tag{14}$$

Notice that when $\|\overline{b}\| = \|b\|$ this process fails and we simply set $\varepsilon^{k+1} := +\infty$. Note that this is a rather peculiar pathological situation, as it could only happen if all variables have values equal to one of their bounds, which would imply that we have $n+1$ active constraints at x^k. Now, to state our hybrid strategy, we evaluate whether the heuristic in computing x^k by (4) using the Euclidean projection is efficient in reducing the KKT-residual at each iteration, that is, if $\varepsilon^{k+1} \leq \gamma \varepsilon^k$ where $\gamma < 1$ is predefined. If so, we continue with the heuristic, otherwise we switch to solving the augmented Lagrangian subproblem (3). The full algorithm with this modification is stated below.

Algorithm 1 Hybrid augmented Lagrangian algorithm for the resource allocation problem

Step 0. Choose $\lambda_{min} \in \mathbb{R}$, $\lambda_{max} \in \mathbb{R}$, $\lambda^0 \in [\lambda_{min}, \lambda_{max}]$, $\gamma < 1$, $r_0 > 0$, $\theta \in (0,1)$, $\beta > 1$, $k_0 \geq 0$, and $\varepsilon \geq 0$, and set $k := 0$.

Step 1. If $k \leq 1$ or $\varepsilon^k \leq \gamma\varepsilon^{k-1}$, compute the iterate x^k according to the following procedure:

1.1) Find $\bar{x}^k$ as a solution of $\min\{L(x, \lambda_k, r_k) : x \in \mathbb{R}^n\}$.

1.2) Compute using the Euclidean projection:

$$x^k = \Pi_{[\ell,u]}(\bar{x}^k - \nabla_x L(\bar{x}^k, \lambda_k, r_k)).$$

Otherwise, switch to a standard augmented Lagrangian method, that is, from this point onwards, this step consists of finding x^k by approximately solving subproblem (3) by any method of choice.

Step 3. Compute a new approximation of the Lagrange multiplier, according to:

$$\lambda_{k+1} = \max\{\lambda_{min}, \min\{\lambda_{max}, \lambda_k + r_k(b^T x^k - c)\}\}.$$

Step 4. Update the penalty parameter:

$$r_{k+1} = \begin{cases} r_k, & \text{if } k \leq k_0 \text{ or } |h(x^k)| \leq \theta |h(x^{k-1})| \\ \beta r_k, & \text{otherwise} \end{cases}$$

where $h(x) = b^T x - c$.

Step 5. Compute the KKT residual: Use the least squares procedure described to compute λ and μ (formulas (12) and (13)), and compute ε^{k+1} by (14).

Step 6. Test the stopping criterion: If $|b^T x^k - c| < \varepsilon$ and $\|x^k - x^{k-1}\| < \varepsilon$, then stop. Otherwise set $k := k + 1$ and return to **Step 1**.

The next result states that the hybrid procedure given by Algorithm 1 converges to a solution of problem (2).

Theorem 2.1 *The sequence $\{x^k\}$ generated by Algorithm 1 converges to a solution of the original Problem* (2).

Proof: Indeed, if $\varepsilon^k > \gamma\varepsilon^{k-1}$ on an interaction, then the convergence is guaranteed by the standard method in Step 3 (see Theorem 5.2 in [Birgin and Martinez (2014)]), therefore, we can assume that $\varepsilon^k \to 0$, meaning that $Px^k - a + \lambda b + \mu \to 0$. This implies that the sequential approximate KKT (AKKT) condition is satisfied.

In addition, the feasibility is guaranteed by construction, by Step 1.

Also, since the multiplier components $\overline{\mu}$ are redefined as $\overline{\mu}_i := \max\{0, \overline{\mu}_i\}$ when $(x^k)_i = u_i$, and $\overline{\mu}_i := \min\{0, \overline{\mu}_i\}$ when $(x^k)_i = \ell_i$ for all $i \in I$, we also guarantee the complementarity inequalities.

In other words, the sequence converges to an approximate AKKT point for Problem (2), and since there is only one linear constraint, we have that the sequence converges to a solution of Problem (2) (see for instance [Andreani et. al. (2009)]). $\square$

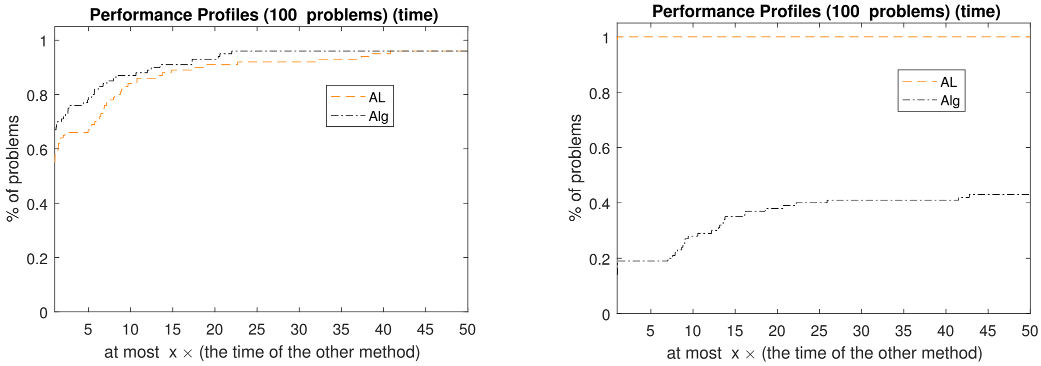
3 Numerical Experiments

In this section we perform some numerical experiments illustrating the robustness and effectiveness of Algorithm 1 and a variation of it which we describe later. All the experiments were ran with Matlab on an Intel Core i7-8565U 1.99 GHz. The objective of this experiments is showing both that the original algorithm of [Torrealba et al. (2021)] may fail on the general quadratic when using the Euclidean projection as well as illustrating that the hybrid approach performs well on all cases. In all tests the original algorithm of [Torrealba et al. (2021)] was ran with the Euclidean projection.

In our first test, we illustrate that the original method in [Torrealba et al. (2021)] may either perform well or very poorly depending on the structure of the problem. We select two sets of problems and run the algorithm proposed in [Torrealba et al. (2021)] (abbreviated `Alg`), which corresponds to Algorithm 1 but where **Step 1** is always computed using the heuristic approach (4), never switching to solving subproblem (3). We compare it with a standard augmented Lagrangian approach (abbreviated `AL`), where **Step 1** of Algorithm 1 is replaced by directly solving subproblem (3) at every iteration, using Matlab's optimization toolbox with standard settings.

In each set of problems, we chose 100 randomly generated convex quadratic objective functions with structure defined as in (5). For each problem, entries of vector a were randomly generated in the interval $[0, 1]$, while constraint vector b and the initial point to run each method were taken as e, the vector of ones in $\mathbb{R}^n$, with $n = 500$. Entries of matrix P were randomly generated on $[0, 0.1]$, with P being redefined as $P^T P + I$ in order to ensure positive definiteness. For both methods we used $\varepsilon = 10^{-4}$, $\gamma = 0.9$, and k_0 was chosen large enough so that $r = 1$ was maintained constant, as in the implementation in [Torrealba et al. (2021)]. This also dismisses the choice of the parameters θ and β. Finally, for the first set of 100 problems we considered the constraints defined by the box $[\ell, u] = [-\frac{n}{2}e, \frac{n}{2}e]$ with $c = 0$, while for the second set of 100 problems we considered a displacement of this constraint by considering $[\ell, u] = [0, ne]$ and $c = n$. Finally, in **Step 6**, we considered an additional stopping criterion of a maximum of 1000 iterations for both methods.

In Figure 1a) we show the performance profile of the results on the first set of problems while Figure 1b) shows the correspondent results on the second set of problem. We can see that `Alg` is able to compete with `AL` in the first set of problems, being slightly more efficient and solving almost all problems. However, in the second test, `Alg` performed considerably poorer than `AL`, being able to solve only circa 40% of the problems in less than 50 times the time taken by `AL`.



(a) Set 1: $[\ell, u] = [-\frac{n}{2}e, \frac{n}{2}e]$ and $c = 0$.

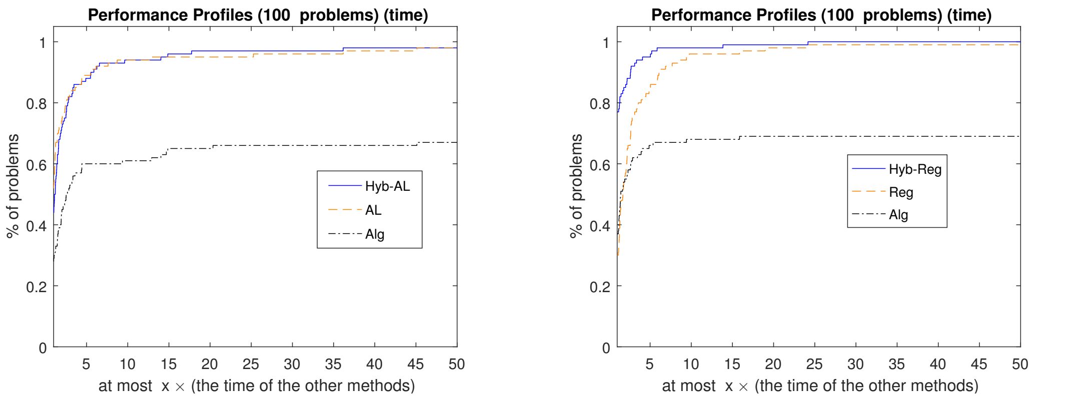
(b) Set 2: $[\ell, u] = [0, ne]$ and $c = n$.

Figure 1: Comparison of the standard augmented Lagrangian (`AL`) and the heuristic approach proposed in [Torrealba et al. (2021)] (`Alg`) on two sets of constraints and 100 randomly generated convex problems.

Figure 1 illustrates that the performance of the algorithm in [Torrealba et al. (2021)] may drastically depend on the structure of the problem, which emphasizes the need of considering the hybrid approach of Algorithm 1 instead. It also suggests that the convergence theory of this method with the Euclidean projection should be further investigated in the sense of detecting larger classes of problems where the algorithm is able to perform well. Notice that in the test set depicted in Figura 1a), the method is still able to perform quite well despite the fact that the euclidean projection does not coincide with the projection with respect to the P-norm.

In our second test, we considered the behavior of the hybrid approach we presented in Algorithm 1 (which we abbreviate as `Hyb-AL`) in comparison with the standard augmented Lagrangian approach (`AL`) and the original algorithm in [Torrealba et al. (2021)] (`Alg`). The test set is choosen similarly as before but with a mixture of constraints where `Alg` behaves well or poorly, that is, we considered 50 randomly generated problems with the structure described in Figure 1a) and 50 randomly generated problems as described in Figure 1b). The results are shown in Figure 2a) where we can see that `Hyb-AL` is able to quickly switch to the standard augmented Lagrangian whenever the heuristic is failing without hindering its performance.

Finally, in Figure 2b), we present the results on this same test of problems but considering a different method instead of the augmented Lagrangian approach. That is, we considered Algorithm 1 but in **Step 1**, when the heuristic approach fails in reducing the KKT-residual, we stop the execution and resort to a different method from this point onwards. The method we considered is a version of the multiplier search method as described in [Bretthauer and Shetty (2002)], where the idea is solving the equation $b^T x(\lambda) = c$ using a root finding algorithm, where $x(\lambda)$ is the projection onto the box constraint of the solution x of $Px - a + \lambda b = 0$. We used the Regula Falsi method as the root finding algorithm (see [Bretthauer and Shetty (2002)] for details). We then compare the hybrid algorithm built in this way (`Hyb-Reg`), the original algorithm of [Torrealba et al. (2021)] (`Alg`), and the pure multiplier search method (`Reg`), where the results are shown in Figure 2b). There, we can see that the proposed heuristic is able to accelerate the multiplier search method considerably, being the most efficient method for circa 80% of the problems.



(a) Comparison with augmented Lagrangian strategy (b) Comparison with multiplier method using regula falsi

Figure 2: Comparison of the heuristic approach proposed in [Torrealba et al. (2021)] (`Alg`), the hybrid strategy (`Hyb-AL` or `Hyb-Reg`) based on Algorithm 1, and the respective pure solver (`AL` or `Reg`) on a collection of 100 randomly generated problems from a mixture of constraints from both sets of problems described in Figure 1.

In Figure 2 we can see that the hybrid approach is able to accelerate the method of choice, switching to the original method once it detects failure of the heuristic. This is done in such a way that, even when the heuristic fails, the extra work at each step is negligible in comparison with the computation done by the original method. Thus our heuristic approach is able to preserve robustness of the original method while also carrying out the efficiency of the heuristic approach.

In the last experiment, we illustrate that the original algorithm (and by extension, the hybrid algorithm) may perform better than the augmented Lagrangian in some cases. This happens for instance on problems where the P-norm coincides with the Euclidean norm such as the ones in Section 4.1 of [Torrealba et al. (2021)]. However, for random diagonal matrices, which not necessarily have the P-norm coinciding with the Euclidean norm, our experiments showed that the original algorithm may also outperform the classical augmented Lagrangian despite not having theoretical support.

We run the original algorithm of [Torrealba et al. (2021)] (`Alg`), the augmented Lagrangian (`AL`), and the hybrid method (`Hyb-AL`) such as in the experiments reported in Figure 2a). However, we generated 100 problems of dimension $n = 1000$ with box $[\ell, u] = [0, e]$, $c = 0$, and P a random matrix with entries generated in the same way as before. The difference is that with a probability of 50%, we replace P by its diagonal. The expectation is that on a mixed profile like that, the hybrid algorithm would make the most of the original and the augmented Lagrangian counterparts for each type of problem (full or diagonal). For the rest of the parameters we used the same as in the previous experiments. We report the results in Figure 3. We see that indeed the hybrid algorithm outperforms both the augmented Lagrangian and the heuristic approach in this profile.

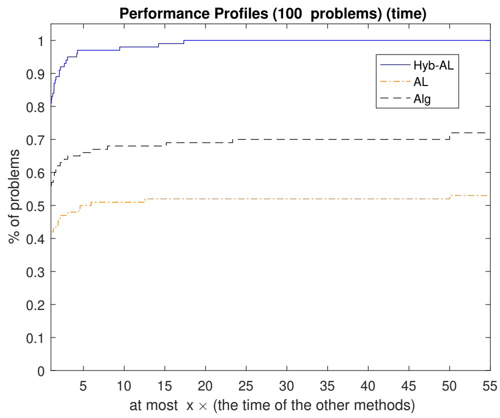


Figure 3: Comparison of the heuristic approach proposed in [Torrealba et al. (2021)] (`Alg`), the hybrid strategy (`Hyb-AL`) described in Algorithm 1, and the augmented Lagrangian method (`AL`) on a collection of 100 randomly generated problems with a 50% chance of having a diagonal structure.

4 Conclusions

In this note we highlight that in the paper [Torrealba et al. (2021)], two different projections are being used somewhat loosely, where they suggest, instead of solving an augmented Lagrangian subproblem, to first solve an unconstrained version of it and then project its solution onto its corresponding feasible set. In the quadratic case, the paper shows convergence by means of using the projection with respect to the P-norm, where P is the Hessian of the objective function, however there is no easy way to compute this. In their numerical experiments, the Euclidean projection is used without much explanation, where the algorithm behaves well. We can explain their results by noticing that they considered mostly the case where P is a multiple of the identity, which guarantees that both projections are the same.

Thus we suggested a hybrid strategy combining computation of the iterate using the Euclidean projection and a standard augmented Lagrangian method. A new efficient procedure to measure the success of the computation of the iterate taking the KKT conditions of the problem into consideration is devised, which gives a cheap criterion for switching to the standard augmented Lagrangian or any other method of choice whenever the heuristic approach is failing. In our numerical experiments we show that this strategy was successful in accelerating the standard augmented Lagrangian method and the multiplier search method.

On the case that P is not diagonal, our tests show that for certain positions of the box (Figure 1a)), the procedure works well despite the inconsistency on the projections. Nevertheless, it is still not clear whether one can find a full class of problems where the Euclidean projection is different from the projection with respect to the P-norm, yet the approach of [Torrealba et al. (2021)] may be proved to work without using a safeguarding procedure. This topic makes for interesting further investigation.

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