Supplementary note to the paper titled "A Convergent 3-Block Semi-Proximal Alternating Direction Method of Multipliers for Conic Programming with 4-Type Constraints"

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October 21, 2014

The purpose of this note is to illustrate the performance of various variants of ADMM which can be employed to solve an SDP problem of the form:

$$\text{(P)} \quad \min\left\{\langle c,\, x\rangle + \delta_{\mathcal{K}}(x) + \delta_{\mathcal{K}_{\mathcal{P}}}(x) \mid \mathcal{A}_E x - b_E = 0\right\},$$

where $\mathcal{K} = \mathcal{S}^n_+$ and $\mathcal{P} = \{X \in \mathcal{S}^n \mid X \geq 0\}$. Its associate dual SDP is given by

$$\text{(D)} \quad \min\left\{\delta_{\mathcal{K}^*}(s) + \delta_{\mathcal{K}_p^*}(z) - \langle b_E,\, y_E\rangle \mid s + z + \mathcal{A}_E^* y_E = c\right\}.$$

Observe that (D) is naturally partition into three blocks of variables (s, z, y).

By using the framework of the 2-block semi-proximal ADMM proposed in [9] (presented as Algorithm sPADMM2 below) for solving the following convex problem

$$\min\left\{f(y) + g(z) \mid \mathcal{F}^* y + \mathcal{G}^* z = c\right\},$$

one can derive various variants of ADMM for solving either (P) or (D).

ADMM2-Prim It is derived by applying the classical ADMM directly (with $\tau = 1.618$ and $\mathcal{S} = 0$, $\mathcal{T} = 0$) to the follwing equivalent primal problem:

$$\min\left\{\langle c,\, x\rangle + (\delta_{\mathcal{K}}(u) + \delta_{\mathcal{K}_{\mathcal{P}}}(v)) \mid \begin{pmatrix} \mathcal{A}_E \\ -I \\ -I \end{pmatrix} x + \begin{pmatrix} 0 & 0 \\ I & 0 \\ 0 & I \end{pmatrix} \begin{pmatrix} u \\ v \end{pmatrix} = \begin{pmatrix} b_E \\ 0 \\ 0 \end{pmatrix}\right\}.$$

This is a convex problem with two blocks of variables with x as the first block and and (u, v) as the second block.

sPADMM2-Prim It is derived by applying sPADMM2 (with $\tau = 1.618$ and an appropriately chosen $\mathcal{S} \succeq 0$, $\mathcal{T} = 0$) to the follwing equivalent primal problem:

$$\min\left\{(\langle c,\, x\rangle + \delta_{\mathcal{K}}(x)) + \delta_{\mathcal{K}_{\mathcal{P}}}(v) \mid \begin{pmatrix} \mathcal{A}_E \\ -I \end{pmatrix} x + \begin{pmatrix} 0 \\ I \end{pmatrix} v = \begin{pmatrix} b_E \\ 0 \end{pmatrix}\right\}.$$

ADMM2. It is derived by applying sPADMM2 (with $\tau = 1.95$ and an appropriately chosen $\mathcal{S} \succeq 0$. The convergence of the algorithm with this larger step-length is guaranteed as the objective on the (y_E, z)-part is linear) to the following equivalent dual problem:

$$\min\left\{(\delta_{\mathcal{K}^*}(s) + \delta_{\mathcal{K}_p^*}(u)) - \langle b_E,\, y_E\rangle \mid \begin{pmatrix} s \\ u \end{pmatrix} + \begin{pmatrix} z + \mathcal{A}_E^* y_E \\ -z \end{pmatrix} = \begin{pmatrix} c \\ 0 \end{pmatrix}\right\}.$$

ADMM3c Our convergent semi-proximal ADMM algorithm (with $\tau = 1.618$) solving (D). It is derived from sPADMM2 with $\mathcal{S} = 0$ and an appropriately chosen $\mathcal{T} \succeq 0$.

ADMM3g A convergent ADMM algorithm (with Gaussian back substitution) proposed in [B. He, M. Tao, and X. Yuan, SIAM Journal on Optimization, 22 (2012), pp. 313–340] that is applied directly to (D).

Algorithm sPADMM2: A generic 2-block semi-proximal ADMM.

Choose appropriate positive semidefinite linear operators $\mathcal{S}$ and $\mathcal{T}$. Let $\sigma > 0$ and $\tau \in (0, \infty)$ be given parameters. Choose $y^0 \in \mathrm{dom}(f)$, $z^0 \in \mathrm{dom}(g)$, and $x^0 \in \mathcal{X}$. Perform the kth iteration as follows:

Step 1. Compute $y^{k+1} = \arg\min L_\sigma(y, z^k; x^k) + \dfrac{\sigma}{2}\|y - y^k\|^2_{\mathcal{S}}$.

Step 2. Compute $z^{k+1} = \arg\min L_\sigma(y^{k+1}, z; x^k) + \dfrac{\sigma}{2}\|z - z^k\|^2_{\mathcal{T}}$.

Step 3. Compute $x^{k+1} = x^k + \tau\sigma(\mathcal{F}^* y^{k+1} + \mathcal{G}^* z^{k+1} - c)$.

In the literature, there are three types of 2-block ADMM:

(a) The classic (generic, common, standard, ...) ADMM takes $\mathcal{S} = 0$ and $\mathcal{T} = 0$ in Algorithm sPADMM2.

(b) The classic (generic, common, standard, ...) proximal ADMM takes positive definite proximal terms $\mathcal{S} \succ 0, \mathcal{T} \succ 0$.

(c) The semi-proximal ADMM, i.e., Algorithm sPADMM2, does not need either $\mathcal{S}$ or $\mathcal{T}$ to be positive definite, and they need only to be positive semidefinite.

While both (a) and (b) have a long history, (c) is a relatively recent addition appearing in Appendix B of [9] in 2013. Though version (c) is the most versatile algorithm, it was hardly known to the ADMM community before the publication of this paper. As mentioned in Section 2 of the paper, the most important ADMM used in this paper is version (c), by taking $\mathcal{S}$, $\mathcal{T}$ to be only positive semidefinite but not positive definite and $\tau > 1$ (in particular, $\tau = 1.618$).

Figure 1 shows the performance profiles of ADMM3c, ADMM2, ADMM3g, ADMM-Prim and sPADMM2-Prim for a total of about 170 problems tested in Section 5.1.2 of the paper. From the performance profiles, one can safely conclude that among all the ADMM-type algorithms our newly proposed ADMM3c is the most suitable, if not the best possible, for solving SDPs.

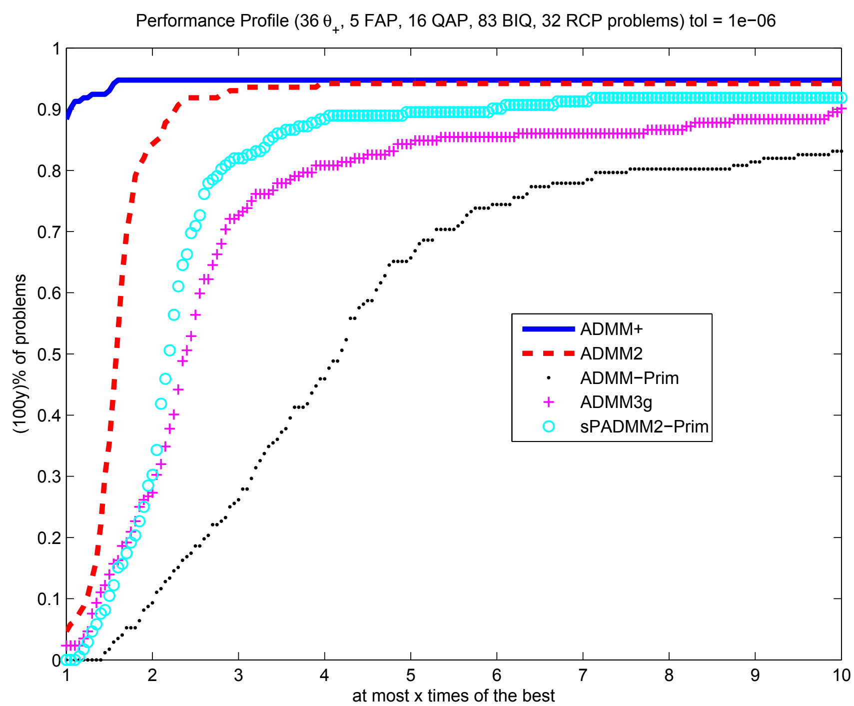

Figure 1: Performance profiles of ADMM3c, ADMM2, ADMM3g, ADMM-Prim and sPADMM2-Prim on $[1, 10]$