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A FORWARD-BACKWARD VIEW OF SOME PRIMAL-DUAL OPTIMIZATION METHODS IN IMAGE RECOVERY

P. L. Combettes, L. Condat, J.-C. Pesquet, and B. C. Võ

1 Sorbonne Universités – UPMC Univ. Paris 06 – Laboratoire Jacques-Louis Lions, Paris, France
2 University of Grenoble–Alpes, GIPSA-lab, St Martin d’Hères, France
3 Université Paris-Est, LIGM, UMR CNRS 8049, Marne-la-Vallée, France
4 LCSL, Istituto Italiano di Tecnologia and MIT, Genova, Italy

ABSTRACT
A wide array of image recovery problems can be abstracted into the problem of minimizing a sum of composite convex functions in a Hilbert space. To solve such problems, primal-dual proximal approaches have been developed which provide efficient solutions to large-scale optimization problems. The objective of this paper is to show that a number of existing algorithms can be derived from a general form of the forward-backward algorithm applied in a suitable product space. Our approach also allows us to develop useful extensions of existing algorithms by introducing a variable metric. An illustration to image restoration is provided.

Index Terms— convex optimization, duality, parallel computing, proximal algorithm, variational methods, image recovery.

1. INTRODUCTION

Many image recovery problems can be formulated in Hilbert spaces \( \mathcal{H} \) and \((\mathcal{G}_i)_{1 \leq i \leq m}\) as structured optimization problems of the form

\[
\min_{x \in \mathcal{H}} \sum_{i=1}^{m} g_i(L_ix),
\]

where, for every \( i \in \{1, \ldots, m\} \), \( g_i \) is a proper lower semi-continuous convex function from \( \mathcal{G}_i \) to \( [-\infty, +\infty] \) and \( L_i \) is a bounded linear operator from \( \mathcal{H} \) to \( \mathcal{G}_i \). For example, the functions \( (g_i \circ L_i)_{1 \leq i \leq m} \) may model data fidelity terms, smooth or nonsmooth measures of regularity, or hard constraints on the solution. In recent years, many algorithms have been developed to solve such a problem by taking advantage of recent advances in convex optimization, especially in the development of proximal tools (see [12, 29] and the references therein). In image processing, however, solving such a problem still poses a number of conceptual and numerical challenges. First of all, one often looks for methods which have the ability to split the problem by activating each of the functions through elementary processing steps which can be computed in parallel. This makes it possible to reduce the complexity of the original problem and to benefit from existing parallel computing architectures. Secondly, it is often useful to design algorithms which can exploit, in a flexible manner, the structure of the problem. In particular, some of the functions may be Lipschitz differentiable in which case they should be exploited through their gradient rather than through their proximity operator, which is usually harder to implement (examples of proximity operators with closed-form expression can be found in [6, 12]). In some problems, the functions \( (g_i)_{1 \leq i \leq m} \) can be expressed as the infimal convolution of simpler functions (see [9] and the references therein). Last but not least, in image recovery, the operators \( (L_i)_{1 \leq i \leq m} \) may be of very large size so that their inverses are costly (e.g., in reconstruction problems). Finding algorithms which do not require to perform inversions of these operators is thus of paramount importance.

Note that all the existing convex optimization algorithms do not have these desirable properties. For example, the Alternating Direction Method of Multipliers (ADMM) [18, 17, 20] requires a stringent assumption of invertibility of the involved linear operator. Parallel versions of ADMM [28] and related Parallel Proximal Algorithm (PPXA) [11, 25] usually necessitate a linear inversion to be performed at each iteration. Also, early primal-dual algorithms [4, 5, 7, 10, 16, 21] did not make it possible to handle smooth functions through their gradients. Only recently, have primal-dual methods been proposed with this feature. Such work was initiated in [13] in the line of [4] and subsequent developments can be found in [2, 3, 8, 9, 15, 27, 30]. As will be seen in the present paper, another advantage of these approaches is that they can be coupled with variable metric strategies which can potentially accelerate their convergence.

In Section 2, we provide some background on convex analysis and monotone operator theory. In Section 3, we introduce a general form of the forward-backward algorithm which uses a variable metric. This algorithm is employed in Section 4 to develop a versatile family of primal-dual proximal methods. Several particular instances of this framework are discussed. Finally, we provide illustrative numerical results in Section 5.

2. NOTATION AND BACKGROUND

Monotone operator theory [1] provides a both insightful and elegant framework for dealing with convex optimization problems and developing new solution algorithms that could not be devised using purely variational tools. We summarize a number of related concepts that will be needed.

Throughout, \( \mathcal{H} \), \( \mathcal{G} \), and \((\mathcal{G}_i)_{1 \leq i \leq m}\) are real Hilbert spaces. We denote the scalar product of a Hilbert space by \( \langle \cdot | \cdot \rangle \) and the associated norm by \( \| \cdot \| \). The symbol \( \rightharpoonup \) denotes weak convergence, and \( \Id \) denotes the identity operator. We denote by \( \mathcal{B}(\mathcal{H}, \mathcal{G}) \) the space of bounded linear operators from \( \mathcal{H} \) to \( \mathcal{G} \), we set \( \mathcal{S}(\mathcal{H}) = \)

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1In a finite-dimensional space, weak convergence is equivalent to strong convergence.
\[ \{ f \in B(H, H) \mid L = L^* \} \]

where \( L^* \) denotes the adjoint of \( L \).

The Loewner partial ordering on \( S(H) \) is denoted by \( \succeq \). For every \( \alpha \in [0, +\infty] \), we set \( \mathcal{P}_\alpha(H) = \{ U \in S(H) \mid U \succeq \alpha \Id \} \), and we denote by \( \sqrt{\alpha} \) the square root of every \( U \in \mathcal{P}_\alpha(H) \). Moreover, for every \( U \in \mathcal{P}_\alpha(H) \) and \( \alpha > 0 \), we define the norm \( \|U\|_H = \sqrt{\alpha} \).

We denote by \( \mathcal{G} = G_1 \oplus \cdots \oplus G_m \) the Hilbert direct sum of the Hilbert spaces \( (G_1)_{1 \leq i \leq m} \), i.e., their product space equipped with the scalar product \( (x, y) \mapsto \sum_{i=1}^m \langle x_i, y_i \rangle \) where \( x = (x_i)_{1 \leq i \leq m} \) and \( y = (y_i)_{1 \leq i \leq m} \) denote generic elements in \( \mathcal{G} \).

Let \( A : H \to 2^H \) be a set-valued operator. We denote by \( \text{gra } A = \{ (x, u) \in H \times H \mid u \in Ax \} \) the graph of \( A \), and by \( \text{zer } A = \{ x \in H \mid 0 \in Ax \} \) the set of zeros of \( A \). Moreover, \( A \) is monotone if \( (\forall (x, y) \in H \times H)(\forall (u, v) \in Ax \times Ay) \quad (x - y, u - v) \geq 0, \) which allows us to retrieve [14, Theorem 4.1].

Theorem 3.1

\[ \sup_{n \in \mathbb{N}} \|V_n\|_H < +\infty \]

and \( V_{n+1}^2 BV_{1/2} \) is \( \beta \)-coercive. Let \( (\lambda_n)_{n \in \mathbb{N}} \) be a sequence in \( [0, 1] \) such that \( \inf_{n \in \mathbb{N}} \lambda_n > 0 \) and let \( (\gamma_n)_{n \in \mathbb{N}} \) be a sequence in \( [0, 2] \) such that \( \inf_{n \in \mathbb{N}} \gamma_n > 0 \) and \( \sup_{n \in \mathbb{N}} \gamma_n < 2 \beta \). Let \( x_0 \in H \) and let \( (a_n)_{n \in \mathbb{N}} \) and \( (b_n)_{n \in \mathbb{N}} \) be absolutely summable sequences in \( H \).

Then \( x_n \to \pi \) for some \( \pi \in Z \).

At iteration \( n \), variables \( a_n \) and \( b_n \) model numerical errors possibly arising when applying \( J_{\gamma_n} V_n A \) or \( B \). Note also that, if \( B = \mu \)-coercive with \( \mu \in [0, +\infty] \), one can choose \( \beta = \mu(\sup_{n \in \mathbb{N}} \|V_n\|_H)^{-1} \), which allows us to retrieve [14, Theorem 4.1]. In the next section, we shall see how a judicious use of this result allows us to derive a variety of flexible convex optimization algorithms.

4. A VARIABLE METRIC PRIMAL-DUAL METHOD

4.1. Formulation

A wide array of optimization problems encountered in image processing are instances of the following one, which was first investigated in [13] and can be viewed as a more structured version of the minimization problem in (1):

**Problem 4.1**

Let \( z \in H \), let \( m \) be a strictly positive integer, let \( f \in \Gamma_0(H) \), and let \( h : H \to \mathbb{R} \) be convex and differentiable with a Lipschitzian gradient. For every \( i \in \{1, \ldots, m\} \), let \( r_i \in \mathcal{G}_i \), let \( g_i \in \Gamma_0(\mathcal{G}_i) \), let \( \ell_i \in \Gamma_0(\mathcal{G}_i) \) be strongly convex,\(^2\) and suppose that \( 0 \neq L_i \in B(\mathcal{G}_i, \mathcal{G}_i) \). Suppose that

\[ z \in \text{ran} \left( \partial f + \sum_{i=1}^m L_i^*(\partial g_i \circ \partial \ell_i)(L_i \cdot -r_i) + \nabla h \right). \]

Consider the problem

\[ \min_{x \in H} f(x) + \sum_{i=1}^m (g_i \circ \ell_i)(L_i x - r_i) + h(x) - \langle x, z \rangle, \]

and the dual problem

\[ \min_{v_i \in \mathcal{G}_1, \ldots, v_m \in \mathcal{G}_m} \left( f^* \circ h^* \right) \left( z - \sum_{i=1}^m L_i^* v_i \right) + \sum_{i=1}^m (g_i^*(v_i) + \ell_i^*(v_i) + \langle v_i, r_i \rangle). \]

\(^2\)For every \( i \in \{1, \ldots, m\} \), \( \ell_i \) is \( \nu_i^{-1} \)-strongly convex with \( \nu_i \in [0, +\infty] \) if and only if \( \ell_i^2 \) is \( \nu_i \)-Lipschitz differentiable [1, Theorem 18.15].
4.2. A first class of primal-dual algorithms

Let $\alpha \in [0, +\infty[$, let $(U_n)_{n \in \mathbb{N}}$ be a sequence in $\mathcal{P}_n(\mathcal{H})$ such that $(\forall n \in \mathbb{N})$ $U_{n+1} \geq U_n$. For every $i \in \{1, \ldots, m\}$, let $(U_{i,n})_{n \in \mathbb{N}}$ be a sequence in $\mathcal{P}_n(\mathcal{G}_i)$ such that $(\forall n \in \mathbb{N})$ $U_{i,n+1} \geq U_i$. A first possible choice for $(V_n)_{n \in \mathbb{N}}$ is given by

$$\forall n \in \mathbb{N} \quad V_n^{-1} : (x, v) \mapsto (U_n^{-1} x - L^* v, -Lx + \tilde{U}_n^{-1} v)$$

where

$$\tilde{U}_n : \mathcal{G} \to \mathcal{G} : (v_1, \ldots, v_m) \mapsto (U_{1,n} v_1, \ldots, U_{m,n} v_m).$$

The following result constitutes a direct extension of [14, Example 6.4]:

**Proposition 4.2** Let $x_0 \in \mathcal{H}$ and let $(a_n)_{n \in \mathbb{N}}$ and $(c_n)_{n \in \mathbb{N}}$ be absolutely summable sequences in $\mathcal{H}$. For every $i \in \{1, \ldots, m\}$, let $v_{i,0} \in \mathcal{G}_i$, let $(b_{i,n})_{n \in \mathbb{N}}$ and $(d_{i,n})_{n \in \mathbb{N}}$ be absolutely summable sequences in $\mathcal{G}_i$. For every $n \in \mathbb{N}$, let $\mu_n \in [0, +\infty]$ be a Lipschitz constant of $U_1^{1/2} \circ \tilde{\nabla} h \circ U_1^{1/2}$ and, for every $i \in \{1, \ldots, m\}$, let $\nu_{i,n} \in [0, +\infty]$ be a Lipschitz constant of $U_i^{1/2} \circ \nabla \epsilon_i \circ U_i^{1/2}$. Let $(\lambda_n)_{n \in \mathbb{N}}$ be a sequence in $[0, 1]$ such that $\inf_{n \in \mathbb{N}} \lambda_n > 0$. For every $n \in \mathbb{N}$, set

$$\delta_n = \left( \sum_{i=1}^m \|U_{i,n} L_i \|^{2} \right)^{-1/2} - 1,$$

and suppose that

$$\inf_{n \in \mathbb{N}} (1 + \delta_n) \max_{\mu_n, \nu_{1,n}, \ldots, \nu_{m,n}} > \frac{1}{2}.$$
on an image recovery example. Two observed images $w_1$ (SNR = 5.87 dB) (b), blurred image $w_2$ (SNR = 16.63 dB) (c), and restored image $\tilde{x}$ (SNR = 21.61 dB) (d).

Set

\[ s_n = x_n - U_n(\nabla h(x_n) + c_n - z) \]
\[ y_n = s_n - U_n^T \sum_{i=1}^n L_i^T v_i, \]
\[ q_{i,n} = \text{prox}_{\lambda_i}^{-1}(v_{i,n} + U_i y_n - \nabla \ell_i(v_{i,n})) - d_i - r_i \]
\[ v_{i,n+1} = v_{i,n} + \lambda_n (q_{i,n} - v_{i,n}) \]
\[ p_n = s_n - U_n^T \sum_{i=1}^n L_i^T q_{i,n} \]
\[ x_{n+1} = x_n + \lambda_n (p_n - x_n) \]

(25)

Assume that $f = 0$. Then $(x_n)_{n \in \mathbb{N}}$ converges weakly to a solution to (12), for every $i \in \{1, \ldots, m\}$ $(v_{i,n})_{n \in \mathbb{N}}$ converges weakly to some $\mathfrak{f}_i \in G_i$, and $(\mathfrak{f}_1, \ldots, \mathfrak{f}_m)$ is a solution to (13).

The algorithm proposed in [23, 8] is a special case of the previous one, in the absence of errors, when $m = 1$, $\mathcal{H}$ and $G_1$ are finite dimensional spaces, $\ell_1 = \ell(0)$, $U_n \equiv \tau I_d$ with $\tau \in [0, +\infty]$, $U_{1,n} \equiv \sigma I_d$ with $\sigma \in [0, +\infty]$, and no relaxation ($\lambda_n \equiv 1$) or a constant one ($\lambda_n \equiv \kappa < 1$) is performed.

5. APPLICATION TO IMAGE RESTORATION

We illustrate the flexibility of the proposed primal-dual algorithms on an image recovery example. Two observed images $w_1$ and $w_2$ of the same scene $\mathfrak{f} \in \mathbb{R}^N$ ($N = 256^2$) are available (see Fig. 1(a)-(c)). The first one is corrupted with a noise with a variance $\theta_1^2 = 576$, while the second one has been degraded by a linear operator $H \in \mathbb{R}^{N \times N}$ ($7 \times 7$ uniform blur) and a noise with variance $\theta_2^2 = 25$. The noise components are mutually statistically independent, additive, zero-mean, white, and Gaussian distributed. Note that this kind of multivariate restoration problem is encountered in some push-broom satellite imaging systems.

An estimate $\tilde{x}$ of $\mathfrak{f}$ is computed as a solution to (12) where $m = 2$, $\theta = 0$, $r_1 = 0$, $r_2 = 0$,

\[ h = \frac{1}{\theta_1^2} \| w_1 \|^2 + \frac{1}{\theta_2^2} \| H \cdot w_2 \|^2, \]
\[ g_1 = \lambda_{[0,255]}^2, \quad g_2 = \kappa \| \cdot \|_{1,2}, \]
\[ f = 0, \quad \ell_1 = \ell_2 = \ell(0) \]

(26) (27) (28)

while the second function in (27) denotes the $\ell_{1,2}$-norm and $\kappa \in [0, +\infty]$. In addition, $L_1 = I_d$ and $L_2 = [G_1, G_2]^\top$ where $G_1 \in \mathbb{R}^{N \times N}$ and $G_2 \in \mathbb{R}^{N \times N}$ are horizontal and vertical discrete gradient operators. Function $g_1$ introduces some a priori constraint on the range values in the target image, while function $g_2 \circ L_2$ corresponds to a classical total variation regularization. The minimization problem is solved numerically by using Algorithm (25) with $\lambda_n \equiv 1$. In a first experiment, standard choices of the algorithm parameters are made by setting $U_n \equiv \tau I_d$, $U_{1,n} \equiv \sigma I_d$, and $U_{2,n} \equiv \sigma I_d$ with $\tau, \sigma \in [0, +\infty]$. In a second experiment, a more sophisticated choice of the metric is made. The operators $(U_n)_{n \in \mathbb{N}}$, $(U_{1,n})_{n \in \mathbb{N}}$ and $(U_{2,n})_{n \in \mathbb{N}}$ are still chosen diagonal and constant in order to facilitate the implementation of the algorithm, but the diagonal values are optimized in an empirical manner. A similar strategy was applied in [26] in the case of Algorithm (21). The regularization parameter $\kappa$ has been set so as to get the highest value of the resulting signal-to-noise ratio (SNR).

The restored image is displayed in Fig. 1(d). Fig. 2 shows the convergence profile of the algorithm. We plot the evolution of the normalized Euclidean distance (in log scale) between the iterates and $\tilde{x}$ in terms of computational time (Matlab R2011b codes running on a single-core Intel i7-2620M CPU@2.7 GHz with 8 GB of RAM). An approximation of $\tilde{x}$ obtained after 5000 iterations is used. This result illustrates the fact that an appropriate choice of the metric may be beneficial in terms of speed of convergence.
6. REFERENCES


