A COMPLEX-VALUED MAJORIZE-MINIMIZE MEMORY GRADIENT METHOD WITH APPLICATION TO PARALLEL MRI

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ABSTRACT
Complex-valued data are encountered in many application areas of signal and image processing. In the context of optimization of functions of real variables, subspace algorithms have recently attracted much interest, due to their efficiency in solving large-size problems while simultaneously offering theoretical convergence guarantees. The goal of this paper is to show how some of these methods can be successfully extended to the complex case. More precisely, we investigate the properties of the proposed complex-valued Majorize-Minimize Memory Gradient (3MG) algorithm. An important practical application of these results arises for image reconstruction in Parallel Magnetic Resonance Imaging (PMRI). Comparisons with existing optimization methods confirm the good performance of our approach for PMRI reconstruction.

Index Terms— complex-valued signals, optimization, subspace algorithms, descent methods, majorization-minimization, image reconstruction, inverse problems, magnetic resonance imaging, sampling

1. INTRODUCTION
Complex-valued data are ubiquitous in signal and image processing. As emphasized in [1], dealing with complex-valued signals raises a number of challenging theoretical issues, in particular owing to their existing relations with the theory of analytic functions. Problems involving complex-valued signals are often formulated as the search for a solution satisfying some optimality conditions. Since the related optimization problems usually do not have closed form solutions, efforts have been dedicated to the development of specific iterative algorithms for minimizing real-valued functions of complex variables [2, 3]. However, one shortcoming of existing approaches (e.g. interior point methods) is that they may not be very efficient to deal with large-size problems. Another weakness lies in the lack of theoretical convergence guarantees. For example, popular methods such as the nonlinear conjugate gradient algorithm, which may be quite effective in practice, have only been proved to converge under restrictive assumptions. Proximal splitting [4] and augmented Lagrangian [5] methods offer more flexibility for minimizing possibly nonsmooth objective functions, but they may suffer from slow convergence. In the case of functions of real variables, a recent majorize-minimize (MM) subspace algorithm has been proposed which overcomes these limitations [6, 7]. Note that MM strategies for functions of complex variables were already investigated in [8, 9] but they were restricted to half-quadratic algorithms requiring the inversion of a large-size linear operator, which is not tractable for any acquisition model.

Complex-valued data are involved in several imaging systems such as in Magnetic Resonance Imaging (MRI). Many recent works were directed to the proposal of reconstruction methods for parallel MRI (PMRI) [10, 11, 12, 13, 14]. The objective of PMRI is to reduce the acquisition time while maintaining a good image quality. This is achieved by combining subsampling strategies in the k-space with the use of an array of coils so as to compensate spectral decimation with spatial diversity. Let us emphasize that the design of an appropriate subsampling scheme is strongly related to compressive sensing issues [15, 16]. Among the existing reconstruction approaches based on variational formulations and optimization algorithms, we can mention methods based on iterative soft-thresholding [17] or more elaborate proximal algorithms [11], and augmented Lagrangian techniques [13, 18]. Note that, to the best of our knowledge, MM subspace algorithms have never been used in the context of PMRI.

The organization of the paper is as follows: in Section 2, the addressed optimization problem is formulated in a general manner and our notation is introduced. In Section 3, we recall some classical results about the derivative of real-valued functions of complex variables, which are relevant to this work. Section 4 describes the employed MM strategy in the complex case. The proposed complex-valued 3MG (Majorize-Minimize Memory Gradient) algorithm is studied. In particular, its connections with the algorithm in [6, 7] for minimizing functions of real variables are discussed. Section 5 presents the application of our algorithm to PMRI reconstruction.
2. PROBLEM STATEMENT

In this work, we will consider the following penalized optimization problem:

\[
\min_{x \in \mathbb{C}^N} \quad (F(x) = \Phi(Hx - y) + \Psi(x)),
\]

(1)

where \( H \neq 0 \) is a matrix in \( \mathbb{C}^{Q \times N} \), \( y \) is an observation vector in \( \mathbb{C}^Q \), \( \Phi : \mathbb{C}^Q \rightarrow \mathbb{R} \), and \( \Psi : \mathbb{C}^N \rightarrow \mathbb{R} \). In inverse problems, function \( \Phi \) usually corresponds to a data-fidelity term and \( \Psi \) to a regularization function. We focus on the case when the latter function takes the following form:

\[
(\forall x \in \mathbb{C}^N) \quad \Psi(x) = \sum_{s=1}^{S} \psi_s(|v_s^Hx|)
\]

(2)

where \( |\cdot| \) denotes the complex modulus, \((\cdot)^H\) is the matrix trans-conjugate operation, and, for every \( s \in \{1, \ldots, S\} \), \( \psi_s : \mathbb{R} \rightarrow \mathbb{R} \), and \( v_s \in \mathbb{C}^N \). Note that (2) includes anisotropic total variation and frame analysis penalties as special cases.

**Assumption 1.** Throughout this paper, we suppose that:

(i) \( \psi \) is differentiable.

(ii) For every \( s \in \{1, \ldots, S\} \), \( \psi_s \) is a differentiable function and \( \lim_{t \rightarrow 0} \psi_s(t)/t \in \mathbb{R} \) where \( \psi_s \) denotes the derivative of \( \psi_s \).

The definition in (3) implies that the derivative of \( \Phi(H \cdot -y) \) at \( x \in \mathbb{C}^N \) is \( H^H\nabla \Phi(Hx - y) \). Let us now define

\[
(\forall a \in \mathbb{R}) \quad \omega_s(a) = \begin{cases} \frac{\psi_s(a)}{a} & \text{if } a \neq 0 \\ \lim_{a \rightarrow 0} \psi_s(t)/t & \text{otherwise.} \end{cases}
\]

(4)

It can be easily shown that the Wirtinger derivative of \( \Psi \) is

\[
(\forall x \in \mathbb{C}^N) \quad \nabla \Psi(x) = \frac{1}{2} V \text{ Diag } (b(x)) V^H x
\]

(5)

where \( V = [v_1, \ldots, v_S] \in \mathbb{C}^{N \times S} \) and \( b(x) = (\omega_s(|v_s^Hx|))_{1 \leq s \leq S} \). So, the complex-valued derivative of \( F \) is

\[
(\forall x \in \mathbb{C}^N) \quad \nabla F(x) = H^H \nabla \Phi(Hx - y) + \nabla \Psi(x)
\]

(6)

where the derivative of \( \Psi \) is given by (5).

4. QUADRATIC MAJORIZATION

In order to develop an efficient algorithm for solving Problem (1), we introduce the following additional assumption:

**Assumption 2.**

(i) \( \Phi \) has a \( \beta \)-Lipschitz derivative with \( \beta \in (0, +\infty) \), i.e.

\[
(\forall z \in \mathbb{C}^Q)(\forall z' \in \mathbb{C}^Q) \quad \|\nabla \Phi(z) - \nabla \Phi(z')\| \leq \beta \|z - z'\|.
\]

(7)

(ii) For every \( s \in \{1, \ldots, S\} \), \( \psi_s(\sqrt{r}) \) is concave on \([0, +\infty)\).

(iii) For every \( s \in \{1, \ldots, S\} \), there exists \( \omega_s \in [0, +\infty) \) such that \( (\forall t \in (0, +\infty)) \) \( 0 \leq \omega_s(t) \leq \omega_s \).

Note that Assumption 2(i) is quite standard and, in particular, it is satisfied for least squares data fidelity terms. Assumptions 2(ii) and 2(iii) hold for a wide class of penalty functions, e.g. \( \ell_2-\ell_1 \) convex functions constituting smooth approximations of the \( \ell_1 \) norm [6], or \( \ell_2-\ell_0 \) nonconvex functions providing smooth approximations of the \( \ell_0 \) cost [7].

The following property can then be proved:

**Proposition 1.** Under Assumptions 1 and 2, for every \((x, x') \in (\mathbb{C}^N)^2 \), \( F(x) \leq \Theta(x, x') \), where

\[
\Theta(x, x') = F(x') + 2\text{Re} \left\{ \nabla F(x')^H(x - x') \right\} + \frac{1}{2} (x - x')^H A(x')(x - x')
\]

and \( A(x') = \mu H^HH + V \text{ Diag } (b(x')) V^H \) with \( \mu \in [2\beta, +\infty) \).

Subspace algorithms consist of building a sequence \((x_k)_{k \in \mathbb{N}} \) according to the following iterative scheme:

\[
(\forall k \in \mathbb{N}) \quad x_{k+1} = x_k + D_k u_k,
\]

(8)

where \( D_k \in \mathbb{C}^{N \times M} \) is a subspace search matrix and \( u_k \in \mathbb{C}^M \) is a multivariate step-size minimizing \( u \mapsto F(x_k + D_k u) \) over \( \mathbb{C}^M \). The MM strategy replaces the minimization of the original function \( F \) over the subspace with successive minimizations of quadratic tangent majorants \( u \mapsto \)
for every \( \sum \) a finite length in the sense that \( k \in \) so-called MM Memory Gradient algorithm.

Proposition 2. Assume that \( F \) is a semi-algebraic function such that \( \lim_{\|x\| \to +\infty} F(x) = +\infty \). Under Assumptions 1 and 2, Algorithm (10) generates a sequence \( \{x_k\}_{k \in \mathbb{N}} \) converging to a critical point of \( F \). Moreover, this sequence has a finite length in the sense that \( \sum_{k=0}^{+\infty} \|x_{k+1} - x_k\| < +\infty \).

5. APPLICATION TO PARALLEL MRI

5.1. Model

In parallel MRI, a set of measures \( \{d_\ell\}_{1 \leq \ell \leq L} \) is acquired from \( L \) coils. These measures are related to the original full FOV (Field Of View) image \( \mathbf{p} \in \mathbb{C}^K \) (the image being columnwise reshaped as a vector) corresponding to a spin density. More precisely, the observation model reads:

\[
\langle \forall \ell \in \{1, \ldots, L\} \rangle \quad d_\ell = \Sigma F S_\ell \mathbf{p} + w_\ell
\]

5.2. Simulation results

In our experiments, the reconstruction of a sagittal view of a 3D anatomical image is performed from noisy parallel MRI data generated according to Model (11). The reference image \( \mathbf{p} \) (see Fig. 1 left) is defined as the reconstruction result from a non-accelerated acquisition \( (R = 1) \) obtained with a 3 Tesla Siemens Trio magnet having an \( L = 32 \)-channel receiver coil (no parallel transmission has been used). The data have been acquired using a 3D T1-weighted MP-RAGE pulse sequence. A resampling has been performed in the \( k \)-space by zero-filling in order to facilitate the use of fast wavelet decompositions, so leading to a \( 256 \times 256 \) image size \( (K = 256^2) \).
Estimates of the sensitivity matrices \((S_ℓ)_{1≤ℓ≤L}\) are also available. Different sampling patterns with \(R = 5\), are considered for \(\Sigma\), namely regular line subsampling, uniform random, radial, spiral, with \(\pi\) density [19], and polynomial decay of various orders [15]. Finally, a circular complex Gaussian white noise with variance equal to \(6 \times 10^9\) is added to the data.

Problem (12) is solved by using Algorithm (10) with parameter \(J = 1\). The convex \(ℓ_2-ℓ_1\) penalization function \(ψ_s : t \rightarrow λ_s(\sqrt{T + t^2/κ^2} - 1)\) is employed, for every \(s ∈ \{1, \cdots, S\}\). In the presented results, \((f_s)_{1≤s≤S}\) \((S = K)\) corresponds to an orthonormal wavelet basis using Symmlet filters of length 10, and the decomposition is carried out over 3 resolution levels. For simplicity, the parameters \((λ_s)_{1≤s≤S}\) are equal to the same constant \(λ\) for the detail coefficients, while they have been set to zero for the approximation ones. The parameters \(λ\) and \(δ\) are tuned so as to maximize the Signal-to-Noise Ratio (SNR) between the reference image and its reconstructed version.

Table 1 allows us to evaluate the reconstruction performance of 3MG algorithm in terms of SNR for the different sampling patterns. One can observe that sampling strategies based on low-order polynomial distributions as well as on the uniform or \(π\) distributions lead to higher quality reconstructed images. The modulus of the reconstructed image for Poly1 sampling strategy is displayed in Fig. 1 (right).

We compare the proposed algorithm with state-of-the-art primal-dual convex optimization methods [21, 20, 22] and the Alternating-Direction Method of Multipliers (ADMM) [5, 18, 13] in terms of computation time for Matlab R2011b codes running on a single-core Intel i7-2620M CPU@2.7 GHz with 8 Gb of RAM, in the case of Poly1 sampling strategy. Although an \(ℓ_1\) penalization is used in the other convex optimization approaches, it is worth noticing that the resulting SNR values reported in Table 2 are identical to those provided by 3MG with \(ℓ_2-ℓ_1\). Moreover, as illustrated by Fig. 2, the proposed algorithm benefits from a faster convergence. A further advantage of 3MG is that it allows the use of nonconvex penalizations. In Table 2, we also indicate results obtained for some \(ℓ_2-ℓ_0\) penalizations, namely Geman-McClure (G), Welsh (W) and Hyperbolic tangent (H) potentials (see [7, Sec.2.2]), for which the local convergence of 3MG algorithm is guaranteed. One can observe a quantitative improvement of the reconstruction quality with respect to the convex case.

### 6. CONCLUSION

In this paper, we have proposed an extension of the 3MG algorithm for the resolution of large-size optimization problems involving functions of complex variables. We have shown that the proposed algorithm is guaranteed to converge under weak assumptions. Its good numerical performance has been demonstrated in the context of complex-valued im-

<table>
<thead>
<tr>
<th>Sampling pattern</th>
<th>SNR (dB)</th>
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<tbody>
<tr>
<td>Poly1</td>
<td>19.95</td>
</tr>
<tr>
<td>Poly2</td>
<td>19.34</td>
</tr>
<tr>
<td>Poly3</td>
<td>18.53</td>
</tr>
<tr>
<td>Poly4</td>
<td>17.50</td>
</tr>
<tr>
<td>Poly5</td>
<td>16.95</td>
</tr>
<tr>
<td>Uniform</td>
<td>19.71</td>
</tr>
<tr>
<td>Radial</td>
<td>19.20</td>
</tr>
<tr>
<td>Spiral</td>
<td>19.17</td>
</tr>
<tr>
<td>Regular</td>
<td>18.13</td>
</tr>
<tr>
<td>(π)</td>
<td>19.31</td>
</tr>
</tbody>
</table>

Table 1. SNR values for various subsampling strategies using 3MG algorithm with \(ℓ_2-ℓ_1\) regularization.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Penalization</th>
<th>SNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>M+LFBF [20]</td>
<td>(ℓ_1)</td>
<td>19.95</td>
</tr>
<tr>
<td>CPCV [21, 22]</td>
<td>(ℓ_1)</td>
<td>19.95</td>
</tr>
<tr>
<td>ADMM</td>
<td>(ℓ_1)</td>
<td>19.95</td>
</tr>
<tr>
<td>3MG</td>
<td>(ℓ_2-ℓ_1)</td>
<td>19.95</td>
</tr>
<tr>
<td>3MG</td>
<td>(ℓ_2-ℓ_0) (G)</td>
<td>20.27</td>
</tr>
<tr>
<td>3MG</td>
<td>(ℓ_2-ℓ_0) (W)</td>
<td>20.17</td>
</tr>
<tr>
<td>3MG</td>
<td>(ℓ_2-ℓ_0) (H)</td>
<td>20.05</td>
</tr>
</tbody>
</table>

Table 2. Reconstruction results for several optimization and regularization strategies, for Poly1 subsampling pattern.
age reconstruction from real parallel MRI data.

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7. REFERENCES


