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Amir Beck & Nili Guttman-Beck

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FOM – a MATLAB toolbox of first-order methods for solving convex optimization problems

Amir Beck^{a*} and Nili Guttman-Beck^b

^a*School of Mathematical Sciences, Tel Aviv University, Tel Aviv, Israel;* ^b*School of Computer Science, Academic College of Tel-Aviv Yaffo, Yaffo, Israel*

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This paper presents the FOM MATLAB toolbox for solving convex optimization problems using first-order methods. The diverse features of the eight solvers included in the package are illustrated through a collection of examples of different nature.

Keywords: first-order methods; convex optimization; MATLAB toolbox

MSC Subject Classifications: 65K05; 90C25

1. Introduction

This paper describes the FOM MATLAB toolbox (FOM standing for ‘first-order methods’) comprising eight first-order methods for solving several convex programming models. The purpose of the package is to provide researchers and practitioners a set of first-order methods that are able to solve a variety of convex optimization problems. The solvers utilize computations of (sub)gradients, conjugates, proximal mappings and linear transformations as well as their adjoints. We concentrate on first-order solvers with rigorous and non-asymptotic efficiency estimates of the rate of converge to the optimal value.

There exist several excellent solvers such as SeDuMi [17] and SDPT3 [18] which can be applied to solve *conic* convex optimization problems. CVX [13] is a Matlab-based modelling system for convex optimization that interfaces with these solvers. TFOCS [8] is another recent solver that solves problems that can be cast as convex cone problems using a class of first-order algorithms.

FOM does not assume that the problem possesses any conic structure and is able to tackle convex problems for which the corresponding required oracles are available. Some of the solvers in FOM can also be employed on non-convex problems; see more details in Section 3.5. The software can be downloaded from the website:

<https://sites.google.com/site/fomsolver/home>

The paper is organized as follows. Section 2 gives an overview of the different optimization models and methods that are tackled by FOM along with the corresponding assumptions and

*Corresponding author. Email: becka@tauex.tau.ac.il

Table 1. Models and assumptions of the eight solvers.

MATLAB function	Method	Minimization model	Assumptions	Oracles
prox_subgradient	proximal subgradient	$f(\mathbf{x}) + \lambda g(\mathbf{x})$	$f - \text{lip}$ $g - \text{pc, prx}$ $\lambda > 0$	f, f' $g, \text{prox}_{\alpha g}$
comd	co-mirror descent	$\min_{\mathbf{x} \in X} f(\mathbf{x})$ s.t. $g_i(\mathbf{x}) \leq 0,$	$f - \text{lip}$ $g_i - \text{lip}$ $X - \text{simple}$	f, f' g_i, g'_i
prox_gradient	proximal gradient	$f(\mathbf{x}) + \lambda g(\mathbf{x})$	$f - \text{sm}$ $g - \text{pc, prx}$ $\lambda > 0$	$f, \nabla f$ $g, \text{prox}_{\alpha g}$
sfista	smoothed FISTA	$f(\mathbf{x}) + \lambda_g g(\mathcal{A}\mathbf{x}) + \lambda_h h(\mathbf{x})$	$f - \text{sm}$ $g - \text{pc, prx}$ $h - \text{pc, prx}$ $\lambda_g, \lambda_h > 0$	$f, \nabla f$ $g, \text{prox}_{\alpha g}$ $h, \text{prox}_{\alpha h}$ $\mathcal{A}, \mathcal{A}^T$
adlpm	alternating direction linearized proximal method of multipliers	$f(\mathbf{x}) + \lambda g(\mathcal{A}\mathbf{x})$	$f - \text{pc, prx}$ $g - \text{pc, prx}$ $\lambda > 0$	$f, \text{prox}_{\alpha f}$ $g, \text{prox}_{\alpha g}$ $\mathcal{A}, \mathcal{A}^T$
nested_fista	Nested FISTA	$\varphi(\mathbf{f}(\mathbf{x})) + \lambda g(\mathcal{A}\mathbf{x})$	$\varphi - \text{lip, nd}$ prx $\mathbf{f} - \text{sm}$ $g - \text{pc, prx}$ $\lambda > 0$	$\varphi, \text{prox}_{\alpha \varphi}$ $\mathbf{f}, \nabla \mathbf{f}$ $g, \text{prox}_{\alpha g}$ $\mathcal{A}, \mathcal{A}^T$
fista	FISTA	$f(\mathbf{x}) + \lambda g(\mathbf{x})$	$f - \text{sm}$ $g - \text{pc, prx}$ $\lambda > 0$	$f, \nabla f$ $g, \text{prox}_{\alpha g}$
fdpg	fast dual proximal gradient	$f(\mathbf{x}) + \lambda g(\mathcal{A}\mathbf{x})$	$f - \text{pc, sc}$ $g - \text{pc, prx}$ $\lambda > 0$	$f, \nabla f^*$ $g, \text{prox}_{\alpha g}$ $\mathcal{A}, \mathcal{A}^T$

Notes: We note that the solvers prox_subgradient, prox_gradient, sfista, nested_fista and fista generate feasible iterates in contrast with comd, adlpm and fdpg.

oracles. The solvers are partitioned into three groups that define a certain hierarchy between them. Section 3 offers a variety of examples that demonstrate the strengths and capabilities of the different FOM functions, and provides the user some insights regarding issues such as model, method and parameter choices.

2. Models, methods and underlying assumptions

The eight solvers that comprise the package are listed in Table 1 along with the relevant models they tackle and the required assumptions. Sections 2.1 and 2.2 explain and elaborate on the notation used in the table.

2.1 Assumptions

An underlying assumption that is not written in Table 1 is that *all the involved functions are convex*. In some special cases, non-convex problems can also be treated (see Section 3.5). In addition, the following abbreviations are used to denote properties of functions:

lip ‘Lipschitz’. A function f is Lipschitz if it is Lipschitz continuous over the entire space. That is, there exists an $\ell > 0$ such that

$$|f(\mathbf{x}) - f(\mathbf{y})| \leq \ell \|\mathbf{x} - \mathbf{y}\| \text{ for all } \mathbf{x}, \mathbf{y}.$$

pc ‘proper and closed’.

prx ‘proximable’. A function f is ‘proximable’ if for any positive α , the prox operator of αf given by

$$\text{prox}_{\alpha f}(\mathbf{x}) = \underset{\mathbf{u}}{\operatorname{argmin}} \left\{ \alpha f(\mathbf{u}) + \frac{1}{2} \|\mathbf{u} - \mathbf{x}\|^2 \right\},$$

can be computed efficiently.

sm ‘smooth’. In our context, a function f is considered to be ‘smooth’ if it is differentiable over the entire space and there exists $L > 0$ such that

$$\|\nabla f(\mathbf{x}) - \nabla f(\mathbf{y})\| \leq L \|\mathbf{x} - \mathbf{y}\| \text{ for all } \mathbf{x}, \mathbf{y}.$$

sc ‘strongly convex’. A function f is strongly convex if there exists $\sigma > 0$ such that $f(\mathbf{x}) - (\sigma/2)\|\mathbf{x}\|^2$ is convex.¹

nd ‘non-decreasing’. A function $\varphi : \mathbb{R}^m \rightarrow \mathbb{R}$ is called *non-decreasing* if

$$\varphi(\mathbf{x}) \leq \varphi(\mathbf{y}) \text{ for any } \mathbf{x}, \mathbf{y} \text{ satisfying } \mathbf{x} \leq \mathbf{y}.$$

In addition, the co-mirror descent method requires the underlying set X to be ‘simple’, which here means that it is one of the following four options:

‘simplex’	$X = \left\{ \mathbf{x} \in \mathbb{R}^n : \sum_{i=1}^n x_i = r, \ell_i \leq x_i \leq u_i, i = 1, \dots, n \right\}$
‘ball’	$X = \{\mathbf{x} \in \mathbb{R}^n : \ \mathbf{x} - \mathbf{c}\ _2 \leq r\}$
‘box’	$X = \{\mathbf{x} \in \mathbb{R}^n : \ell_i \leq x_i \leq u_i, i = 1, \dots, n\}$
‘spectahedron’	$X = \{\mathbf{X} \in \mathbb{S}^n : \mathbf{0} \preceq \mathbf{X} \preceq u\mathbf{I}, \operatorname{Tr}(\mathbf{X}) = r\}.$

2.2 Oracles

The solvers require various oracles as inputs, where each oracle is a MATLAB function handle. For a function f and a linear transformation \mathcal{A} , the following oracle notations are used:

- f – function value of f ($\mathbf{x} \mapsto f(\mathbf{x})$);
- f' – a subgradient of f ($\mathbf{x} \mapsto f'(\mathbf{x}) \in \partial f(\mathbf{x})$);
- ∇f – gradient of f ($\mathbf{x} \mapsto \nabla f(\mathbf{x})$);
- ∇f^* – gradient of the conjugate of f ($\mathbf{x} \mapsto \operatorname{argmax}\{\langle \mathbf{u}, \mathbf{x} \rangle - f(\mathbf{u})\}$);
- $\text{prox}_{\alpha f}$ – proximal operator of a positive constant times the function ($(\mathbf{x}, \alpha) \mapsto \text{prox}_{\alpha f}(\mathbf{x})$);
- \mathcal{A} – linear transformation \mathcal{A} ($\mathbf{x} \mapsto \mathcal{A}\mathbf{x}$);
- \mathcal{A}^T – adjoint of \mathcal{A} ($\mathbf{x} \mapsto \mathcal{A}^T \mathbf{x}$).

The proximal (or ‘prox’) operator [15] can be provided by the user, but the package also contains a large amount of implementations of proximal operators (see Table 2). It is also worth mentioning that there are several calculus rules for prox functions (see [1,2]) that can be used in order to generate additional prox mappings which are based on the existing library. If $f = \delta_C$ ($\delta_C(\mathbf{x}) = 0$ for $\mathbf{x} \in C$ and ∞ for $\mathbf{x} \notin C$) with a non-empty closed and convex C , then $\text{prox}_{\alpha f} = P_C$ which is the orthogonal projection operator on C . The orthogonal projections that are implemented in the package are described in Table 3.

Table 2. List of prox functions implemented in the FOM package.

MATLAB function	Function	Assumptions
prox_quadratic	convex quadratic $\alpha(\frac{1}{2}\mathbf{x}^T\mathbf{A}\mathbf{x} + \mathbf{b}^T\mathbf{x})$	$\mathbf{A} \in \mathbb{S}_+^n$
prox_Euclidean_norm*	Euclidean norm $\alpha\ \mathbf{x}\ _2$	
prox_l1*	l_1 - norm $\alpha\ \mathbf{x}\ _1$	
prox_neg_sum_log*	negative sum of logs $-\alpha\sum_{i=1}^n \log x_i$	
prox_linf*	l_∞ - norm $\alpha\ \mathbf{x}\ _\infty$	
prox_max*	maximum $\alpha\max\{x_1, \dots, x_n\}$	
prox_Huber*	Huber $\alpha H_\mu(\mathbf{x}) = \alpha \begin{cases} \frac{1}{2\mu}\ \mathbf{x}\ _2^2 & \ \mathbf{x}\ \leq \mu \\ \ \mathbf{x}\ - \frac{\mu}{2} & \ \mathbf{x}\ > \mu \end{cases}$	$\mu > 0$
prox_sum_k_largest*	sum of k largest values $\alpha\sum_{i=1}^k x_{[i]}$	$k \in \{1, 2, \dots, n\}$
prox_sum_k_largest_abs*	sum of k largest absolute values $\alpha\sum_{i=1}^k x_{(i)} $	$k \in \{1, 2, \dots, n\}$
prox_norm2_linear	l_2 norm of a linear transformation $\alpha\ \mathbf{A}\mathbf{x}\ _2$	\mathbf{A} with full row rank
prox_l1_squared*	squared l_1 - norm $\alpha\ \mathbf{x}\ _1^2$	
prox_max_eigenvalue	maximum eigenvalue $\alpha\lambda_{\max}(\mathbf{X})$	$\mathbf{X} \in \mathbb{S}^n$
prox_neg_log_det	negative log determinant $-\alpha\log(\det(\mathbf{X}))$	$\mathbf{X} \in \mathbb{S}^n$
prox_sum_k_largest_eigenvalues	sum of k largest eigenvalues $\alpha\sum_{i=1}^k \lambda_i(\mathbf{X})$	$\mathbf{X} \in \mathbb{S}^n, k \in \{1, 2, \dots, n\}$
prox_spectral	spectral norm $\alpha\ \mathbf{X}\ _{2,2} = \alpha\sigma_1(\mathbf{X})$	
prox_nuclear	nuclear norm $\alpha\ \mathbf{X}\ _{S_1} = \alpha\sum_{i=1}^{\min\{m,n\}} \sigma_i(\mathbf{X})$	$\mathbf{X} \in \mathbb{R}^{m \times n}$
prox_Ky_Fan	Ky Fan norm $\alpha\ \mathbf{X}\ _{(k)} = \alpha\sum_{i=1}^k \sigma_i(\mathbf{X})$	$\mathbf{X} \in \mathbb{R}^{m \times n}, 1 \leq k \leq \min\{m, n\}$

Notes: All functions assume that α is a positive scalar parameter. Functions marked by * operate on $m \times n$ matrices in the same way they operate on the corresponding mn -length column vector.

2.3 Solvers overview

The eight solvers can be divided into three groups:

- *Group 1.* prox_subgradient, comd.
- *Group 2.* prox_gradient, sfista, adlpm.
- *Group 3.* fista, nested_fista, fdpg.

Table 3. List of orthogonal projection functions implemented in the FOM package.

MATLAB function	Set	Assumptions
proj_Euclidean_ball*	Euclidean ball $B[\mathbf{c}, r] = \{\mathbf{x} : \ \mathbf{x} - \mathbf{c}\ \leq r\}$	$\mathbf{c} \in \mathbb{R}^n, r > 0$
proj_box*	box $\text{Box}[\mathbf{l}, \mathbf{u}] = \{\mathbf{x} : \mathbf{l} \leq \mathbf{x} \leq \mathbf{u}\}$	$\mathbf{l} \leq \mathbf{u}$
proj_affine_set	affine set $\{\mathbf{x} : \mathbf{A}\mathbf{x} = \mathbf{b}\}$	\mathbf{A} with full row rank
proj_halfspace*	half-space $H_{\mathbf{a},b}^- = \{\mathbf{x} : \langle \mathbf{a}, \mathbf{x} \rangle \leq b\}$	$\mathbf{a} \in \mathbb{R}^n \setminus \{\mathbf{0}\}, b \in \mathbb{R}$
proj_two_halfspaces*	intersection of two half-spaces $H_{\mathbf{a}_1, b_1}^- \cap H_{\mathbf{a}_2, b_2}^-$ $= \{\mathbf{x} : \langle \mathbf{a}_1, \mathbf{x} \rangle \leq b_1, \langle \mathbf{a}_2, \mathbf{x} \rangle \leq b_2\}$	$\{\mathbf{a}_1, \mathbf{a}_2\}$ independent
proj_Lorentz	Lorentz cone $L^n = \{\mathbf{x} \in \mathbb{R}^{n+1} : \ \mathbf{x}_{\{1, \dots, n\}}\ \leq x_{n+1}\}$	
proj_hyperplane_box*	intersection of a hyperplane and a box $H_{\mathbf{a},b} \cap \text{Box}[\mathbf{l}, \mathbf{u}]$ $= \{\mathbf{x} : \langle \mathbf{a}, \mathbf{x} \rangle = b, \mathbf{l} \leq \mathbf{x} \leq \mathbf{u}\}$	$H_{\mathbf{a},b} \cap \text{Box}[\mathbf{l}, \mathbf{u}] \neq \emptyset$
proj_halfspace_box*	intersection of a half-space and a box $H_{\mathbf{a},b}^- \cap \text{Box}[\mathbf{l}, \mathbf{u}]$ $= \{\mathbf{x} : \langle \mathbf{a}, \mathbf{x} \rangle \leq b, \mathbf{l} \leq \mathbf{x} \leq \mathbf{u}\}$	$H_{\mathbf{a},b}^- \cap \text{Box}[\mathbf{l}, \mathbf{u}] \neq \emptyset$
proj_simplex*	r -simplex $\Delta_n(r) = \{\mathbf{x} : \mathbf{e}^T \mathbf{x} = r, \mathbf{x} \geq \mathbf{0}\}$ r -full simplex $\Delta_n^+(r) = \{\mathbf{x} : \mathbf{e}^T \mathbf{x} \leq r, \mathbf{x} \geq \mathbf{0}\}$	$r > 0$
proj_product*	product superlevel set $\{\mathbf{x} > \mathbf{0} : \pi_{i=1}^n x_i \geq r\}$	$r > 0$
proj_l1_ball*	l_1 ball $\{\mathbf{x} : \ \mathbf{x}\ _1 \leq r\}$	$r > 0$
proj_l1ball_box*	intersection of weighted l_1 ball and a box $\{\mathbf{x} : \ \mathbf{w} \odot \mathbf{x}\ _1 \leq r, \ \mathbf{x}\ _\infty \leq u\}$	$r, u \geq 0, \mathbf{w} \geq \mathbf{0}$
proj_psd	cone of positive semidefinite matrices $\mathbb{S}_+^n = \{\mathbf{X} : \mathbf{X} \succeq \mathbf{0}\}$	
proj_spectral_box_sym	spectral box (in \mathbb{S}^n) $\{\mathbf{X} \in \mathbb{S}^n : \ell \mathbf{I} \leq \mathbf{X} \leq u \mathbf{I}\}$	$\ell \leq u$, sym. input matrix
proj_spectral_ball	spectral-norm ball $B_{\ \cdot\ _{\mathbb{S}^\infty}}[\mathbf{0}, r] = \{\mathbf{X} : \sigma_1(\mathbf{X}) \leq r\}$	$r > 0$
proj_nuclear_ball	nuclear-norm ball $B_{\ \cdot\ _{\mathbb{S}_1}}[\mathbf{0}, r] = \{\mathbf{X} : \sum_i \sigma_i(\mathbf{X}) \leq r\}$	$r > 0$
proj_spectahedron	r -spectahedron $\Upsilon_n(r) = \{\mathbf{X} \in \mathbb{S}_+^n : \text{Tr}(\mathbf{X}) = r\}$ r -full spectahedron $\Upsilon_n^+(r) = \{\mathbf{X} \in \mathbb{S}_+^n : \text{Tr}(\mathbf{X}) \leq r\}$	$r > 0$, sym. input matrix

Note: Functions marked by * operate on $m \times n$ matrices in the same way they operate on the corresponding mn -length column vector.

The above partition is made according to the known worst-case iteration complexity results of the methods, where group 1 consists of the slowest methods and group 3 consists of the fastest methods. Thus, if several methods can solve a certain problem, it is probably better to choose a method with the highest possible group number. We stress that this division is made according

to the theoretical upper bounds, and that the practical behaviour may be different on specific instances.

The first group consists of two non-smooth solvers: the proximal subgradient [11] and the co-mirror descent [7] methods. Both methods share a complexity of $O(1/\varepsilon^2)$, meaning that the number of iterations required to obtain an ε -optimal (or ε -optimal and feasible)² solution is of an order of $1/\varepsilon^2$.

The second group consists of three solvers: proximal gradient [3,4,9], smoothed FISTA [5] and the alternating direction linearized proximal method of multipliers (ADLPMM) [12,14,16]. These three methods all share an $O(1/\varepsilon)$ complexity, and they are therefore considered to be faster than the methods from the first group, albeit slower than the third group's solvers.

The third group comprises three solvers: FISTA [3,4], nested FISTA, which is a generalization of FISTA to a non-additive composite model (see Appendix) and the fast dual proximal gradient method (FDPG) [6] – all have an $O(1/\sqrt{\varepsilon})$ complexity in terms of function values of the primal or dual problems. One disclaimer to the latter statement is that nested FISTA calls FDPG at each iteration and the $O(1/\sqrt{\varepsilon})$ complexity of nested FISTA is under the assumption that the inner problems are solved exactly.

Most of the methods used in FOM are also described and analysed in the book [2].

3. A tour of FOM

We will not go over the syntax of each of the eight solvers since this will be an extremely tedious and unnecessary task. Detailed explanations on the input and output arguments can be found in the FOM's website: <https://sites.google.com/site/fomsolver/home>. In addition, all the functions are equipped with detailed help notes. For example,

```
>> help prox_subgradient
prox_subgradient employs the proximal subgradient method
for solving the problem  $\min\{f(x) + \lambda g(x)\}$ 

Underlying assumptions:
All functions are convex
f is Lipschitz
g is proper closed and proximable
lambda is a positive scalar
=====
Usage:
out = prox_subgradient(Ffun, Ffun_sgrad, Gfun,
                      Gfun_prox, lambda, startx, [par])
[out, fmin] = prox_subgradient(Ffun, Ffun_sgrad, Gfun,
                              Gfun_prox, lambda, startx, [par])
[out, fmin, parout] = prox_subgradient(Ffun, Ffun_sgrad, Gfun,
                                       Gfun_prox, lambda, startx, [par])
=====
Input:
Ffun      - function handle for the function f
Ffun_sgrad - function handle for the subgradient of the
            function f
Gfun      - function handle for the function g
Gfun_prox - function handle for the proximal mapping of g
            times a positive constant
lambda    - positive scalar penalty for the function g
startx    - starting vector
par       - struct which contains different values required
            for the operation of prox_subgradient

Fields of par:
    max_iter - maximal number of iterations
              [default: 1000]
```

```

eco_flag - true if economic version (without
          calculating objective function values)
          should run, otherwise false
          [default: false]
print_flag - true if internal printing should take
             place, otherwise false [default: true]
alpha      - positive constant determining the stepsize
             of the method (which is alpha/
             sqrt(iternu+1) [default: 1]
eps        - stopping criteria tolerance (the method
             stops when the norm of the difference
             between consecutive iterates is < eps)
             [default: 1e-5]
=====
Output:
out        - optimal solution (up to a tolerance)
fmin       - optimal value (up to a tolerance)
parout     - a struct containing additional information
             related to the convergence.
             The fields of parout are:
iterNum    - number of performed iterations
funValVec  - vector of all function values generated by
             the method

```

We will, however, embark on a tour comprising several examples that will cover most of the features and capabilities of the package, demonstrating also important issues such as model and method choices, as well as questions regarding the input and output parameters.

3.1 Choosing the model

Consider the problem

$$\min_{\mathbf{x} \in \mathbb{R}^4} \{\|\mathbf{Ax} - \mathbf{b}\|_1 + 2\|\mathbf{x}\|_1\}, \quad (1)$$

where \mathbf{A} and \mathbf{b} are generated by the commands

```

>> A = [0.6324    0.9575    0.9572    0.4218;
         0.0975    0.9649    0.4854    0.9157;
         0.2785    0.1576    0.8003    0.7922;
         0.5469    0.9706    0.1419    0.9595];
>> b = [0.6843;    0.6706;    0.4328;    0.8038]

```

The proximal subgradient method (implemented in the MATLAB function `prox_subgradient`) solves problems of the form (see Table 1)

$$\min f(\mathbf{x}) + \lambda g(\mathbf{x}). \quad (2)$$

Obviously, problem (2) fits model (2) with

$$f(\mathbf{x}) = \|\mathbf{Ax} - \mathbf{b}\|_1, g(\mathbf{x}) = \|\mathbf{x}\|_1, \lambda = 2. \quad (3)$$

Note that all the assumptions that f and g need to satisfy according to Table 1 (f – non-smooth convex, g proper closed convex and proximable) are met. The syntax of `prox_subgradient` is

```

[out, fmin, parout] = prox_subgradient(Ffun, Ffun_sgrad, Gfun,
                                       Gfun_prox, lambda, startx, [par])

```

In the specific case of f and g chosen by (7), the input is as follows:

- `Ffun` is a function handle for f [`@(x) norm(A*x-b, 1)`].
- `Ffun_sgrad` is a function handle for a subgradient of f [`@(x) A' * sign(A*x-b)`].

- `Gfun` is a function handle for $g[\|(x)\|_1]$.
- `Gfun_prox` is a function handle for the prox of g times a constant $[\|(x,a)\|_1 \text{prox}_{l1}(x,a)]$.

In this case, the proximal mapping is one of the prox functions implemented in the package (see Table 2 for a complete list). In cases where the prox is not one of the implemented functions, the user can provide its own implementation of the prox.

- `lambda` is equal to 2.
- `startx` is an initial vector, and we will choose it in this example as the zeros vector.

Running the solver yields the following output:

```
>> [out,fmin,parout] =prox_subgradient(@(x) norm(A*x-b,1),@(x) A'*sign(A*x-b), ...
    @(x) norm(x,1), @(x,a)prox_l1(x,a),2,zeros(4,1));
*****
prox_subgradient
*****
#iter      fun. val.
      6      2.526541
      8      2.021784
     10      1.869343
     42      1.858085
      :
     828      1.821805
     901      1.820594
     974      1.820261
-----
Optimal value =      1.820261
```

The proximal subgradient method is not a descent method and only iterations in which an improved (i.e. lower) value was obtained are printed. The array `parout.funValVec` contains all the function values obtained during the execution of the method.

```
>> parout.funValVec
      2.5915
      6.2732
      2.5915
      :
      1.8650
      1.8485
      1.8474
```

A plot of the function values can be generated by the command

```
plot(parout.funValVec)
```

The resulting graph (Figure 1) demonstrates that proximal subgradient is indeed not a descent method.

The best achieved function value is stored in `fmin`

```
>> fmin
fmin =
      1.8203
```

The choice of f and g in (7) is only one option. Another rather straightforward choice is to set

$$f(\mathbf{x}) = \|\mathbf{Ax} - \mathbf{b}\|_1 + 2\|\mathbf{x}\|_1, g(\mathbf{x}) \equiv 0.$$

The parameter λ can be chosen as any positive number; we will arbitrary set it to be one. We can run the proximal subgradient method for the above choice of f and g (recalling that $\text{prox}_{\alpha g}(\mathbf{x}) = \mathbf{x}$ for all $\alpha > 0$ whenever $g \equiv 0$).

```
>> [out,fmin,parout] =prox_subgradient(@(x) norm(A*x-b,1)+2*norm(x,1), ...
    @(x) A'*sign(A*x-b)+2*sign(x), @(x) 0, @(x,a)x,1,zeros(4,1));
```

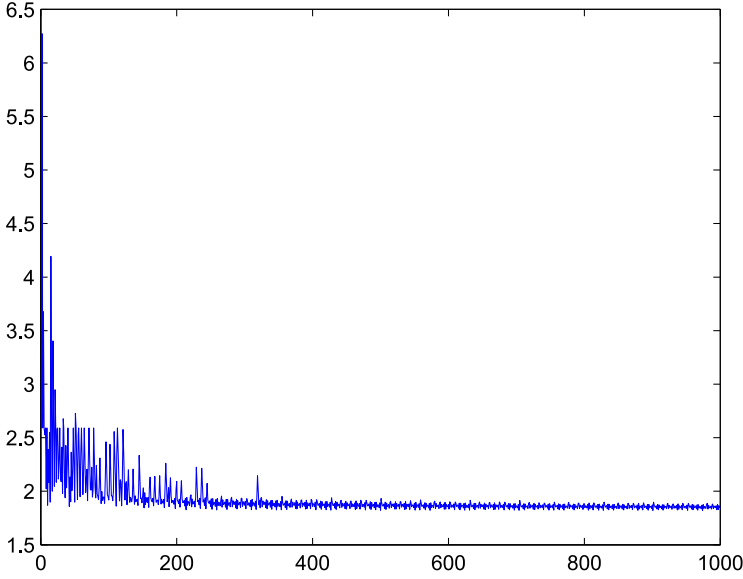


Figure 1. Function values generated by the proximal subgradient method.

```
*****
prox_subgradient
*****
#iter      fun. val.
  73      2.587218
  74      2.280796
  75      1.976423
 200      1.965525
 201      1.937473
 212      1.893150
 214      1.865244
 297      1.856431
 510      1.844707
 643      1.842849
-----
Optimal value =      1.842849
```

Note that the obtained function value (1.8428) is higher than the one obtained in the previous run (1.8203). This is not surprising since the theoretical results of the proximal subgradient method show that the rate of convergence in function values depends on the Lipschitz constant of the function f and not of g [11]. In the second run, the Lipschitz constant of f is larger, and thus the empirical results validate to some extent the known convergence results. Loosely speaking, it is better to put as much as possible from the objective function into g .

3.2 Choosing the solver

It is actually possible to solve problem (1) using the solver `adlpm` from group 2, which should exhibit better performance than `prox_subgradient` from group 1. The solver is a MATLAB implementation of the ‘alternating direction linearized proximal method of multipliers’ algorithm. As can be seen in Table 1, the minimization model that `adlpm` tackles is

$$\min_{\mathbf{x}} f(\mathbf{x}) + \lambda g(\mathcal{A}\mathbf{x}), \quad (4)$$

where both f and g are proper closed, convex, and in addition proximal. Problem (1) fits model (4) with

$$f(\mathbf{x}) = 2\|\mathbf{x}\|_1, \quad g(\mathbf{y}) = \|\mathbf{y} - \mathbf{b}\|_1, \quad \lambda = 1, \quad \mathcal{A}(\mathbf{x}) = \mathbf{A}\mathbf{x}.$$

Note that both f and g are proximal. Indeed, denoting the prox of α times the l_1 -norm function by \mathcal{T}_α (a.k.a. the ‘soft thresholding operator’ [10]):

$$\mathcal{T}_\alpha(\mathbf{x}) \equiv [|\mathbf{x}| - \alpha\mathbf{e}]_+ \odot \text{sgn}(\mathbf{x}),$$

the proximal mappings of αf and αg (for $\alpha > 0$) can be written explicitly as

$$\text{prox}_{\alpha f}(\mathbf{x}) = \mathcal{T}_{2\alpha}(\mathbf{x}), \quad \text{prox}_{\alpha g}(\mathbf{x}) = \mathcal{T}_\alpha(\mathbf{x} - \mathbf{b}) + \mathbf{b}.$$

The syntax of `adlpm` is

```
[out,fmin,parout] = adlpm(Ffun,Ffun_prox,Gfun,Gfun_prox,Afun,Atfun,lambda,
    startx,[L],[par])
```

Note that an optional input parameter is the positive constant L . In fact, L should be chosen as an upper bound on $\|\mathcal{A}\|^2$. In case where $\mathcal{A}\mathbf{x} \equiv \mathbf{A}\mathbf{x}$ for some matrix \mathbf{A} , $\|\mathcal{A}\| = \|\mathbf{A}\|_2$ is the spectral norm of \mathbf{A} . It is highly recommended that user will insert a value of L , since otherwise the solver will find $\|\mathcal{A}\|$ by an inefficient method. It is also important to realize that in general, the function g in the model (8) can be extended real-valued and `adlpm` is not guaranteed to generate a vector in $\text{dom}(g)$. This is the reason why by default the method also computes the feasibility violation of the generated sequence of vectors. It is highly advisable, in cases where g is real-valued, as is the case in this example, to ‘notify’ the solver that g is real-valued by setting `par.real_valued_flag` to `true`. In this setting, the function values calculated by the solver are $f(\mathbf{x}^k) + \lambda g(\mathbf{A}\mathbf{x}^k)$, where \mathbf{x}^k denotes the k th iterate vector.

```
>> clear par;
>> par.real_valued_flag=true;
>> [out,fmin,parout] =adlpm(@(x) 2*norm(x,1),@(x,a)prox_l1(x,2*a),...
    @(x) norm(x-b,1),@(x,a)prox_l1(x-b,a)+b, @(x) A*x, @(x) A'*x,...
    1,zeros(4,1),norm(A)^2,par);
```

```
*****
adlpm
*****
#iter      fun. val.
      2      1.873908
     11      1.870255
     35      1.818719
      :
    575      1.814974
    674      1.814974
    793      1.814974
```

```
Stopping because the norm of the difference between consecutive
iterates is too small
```

```
-----
Optimal value =      1.814974
```

Note that in iteration 35 the method already obtained a better function value than the one obtained by the proximal subgradient method after almost 1000 iterations. This is not a surprising outcome since, as was already noted, `adlpm` belongs to the second group of solvers whereas `prox_subgradient` belongs to the first group.

3.3 Choice of solver in the same group

Consider the problem

$$\min \left\{ \max_{i=1,2,\dots,80} \{\mathbf{a}_i^T \mathbf{x}\} : \mathbf{x} \in \Delta_{50} \right\}, \quad (5)$$

where $\mathbf{a}_1^T, \mathbf{a}_2^T, \dots, \mathbf{a}_{80}^T$ are the rows of an 80×50 matrix generated by the commands

```
>> randn('seed', 315);
>> A=randn(80, 50);
```

One way to solve the problem is to use `prox_subgradient` by setting in its model $(f(\mathbf{x}) + \lambda g(\mathbf{x}))$:

$$f(\mathbf{x}) = \max_{i=1,2,\dots,80} \{\mathbf{a}_i^T \mathbf{x}\}, g(\mathbf{x}) = \delta_{\Delta_{50}}(\mathbf{x}), \quad \lambda = 1.$$

The proximal operator of g is the orthogonal projection onto the unit-simplex, which is implemented in the MATLAB function `proj_simplex` (see Table 3). To solve the problem using `prox_subgradient`, we require a function that computes a subgradient of f . A subgradient of f at \mathbf{x} is given by $\mathbf{a}_{i(\mathbf{x})}$, where $i(\mathbf{x})$ is any member of $\operatorname{argmin}_{i=1,2,\dots,80} \{\mathbf{a}_i^T \mathbf{x}\}$. Following is a MATLAB function implementing a computation of a subgradient of f that should be saved as an m-file called `f_sgrad.m`.

```
function out=f_sgrad(x,A)
[~,i]=max(A*x);
out=A(i,:);
```

Running the solver with 10,000 iterations (the default is 1000) and starting point $(\frac{1}{50}, \frac{1}{50}, \dots, \frac{1}{50})^T$ yields the following output.

```
>> clear par
>> par.max_iter=10000;
>> [out,fmin,parout] =prox_subgradient(@(x)max(A*x),@(x)f_sgrad(x,A),...
    @(x)0, @(x,a)proj_simplex(x),1,1/50*ones(50,1),par);
*****
prox_subgradient
*****
#iter      fun. val.
   344      0.340105
   469      0.304347
   773      0.295849
     :           :
  5857      0.183907
  6592      0.169232
  7047      0.158440
-----
Optimal value =      0.158440
```

It is possible to change some basic parameters of the method that might accelerate (or slow down) the speed of convergence. For example, the stepsize of the proximal subgradient method is given by $\alpha/\sqrt{k+1}$ with k being the iteration index. The default value of α is 1. Changing this value to 0.2 (by setting the value of `par.alpha` to 0.2) yields faster convergence, and consequently a lower function value.

```
>> par.alpha=0.2;
>> [out,fmin,parout] =prox_subgradient(@(x)max(A*x),@(x)f_sgrad(x,A),@(x)0,...
    @(x,a)proj_simplex(x),1,1/50*ones(50,1),par);
*****
prox_subgradient
*****
#iter      fun. val.
```

```

17          0.322719
45          0.298787
91          0.285807
:           :
5675        0.081925
7103        0.074788
9926        0.074581
-----
Optimal value =          0.074581

```

In the context of optimization over the unit-simplex, a better method is the co-mirror descent method implemented in the MATLAB function `comd` whose syntax is

```
[out,fmin,parout] = comd(Ffun,Ffun_sgrad,Gfun,Gfun_sgrad,set,startx,[par])
```

`comd` can also handle additional functional constraints of the form $g_i(\mathbf{x}) \leq 0$ that should be inserted through the input `Gfun`. In our example, there are no additional functional constraints, and thus `Gfun` and `Gfun_sgrad` should both be empty function handles (`[]`). The input `set` in our case is the unit simplex, and thus should be fixed to be `'simplex'`. Running the method for 10,000 iterations gives the following output:

```

>> clear parmd
>> parmd.max_iter=10000;
>> comd(@(x)max(A*x),@(x)f_sgrad(x,A),[],[], 'simplex',1/50*ones(50,1),parmd);
*****
Co-Mirror
*****
#iter      fun. val.
   1         0.350156
   2         0.312403
   4         0.279940
   :         :
 6901        0.050879
 7727        0.050688
 9977        0.050557
-----
Optimal value =          0.050557

```

Clearly, `comd` was able to find a better solution than `prox_subgradient`. It is thus also important to choose the 'correct' method among the solvers from the same group. As a rule of thumb, if the problem at hand fits the model relevant for `comd` (see Table 1), then it is better to use it rather than `prox_subgradient`.

3.4 l_1 -Regularized least squares

Consider the problem

$$\min_{\mathbf{x} \in \mathbb{R}^{100}} \frac{1}{2} \|\mathbf{Ax} - \mathbf{b}\|_2^2 + 2\|\mathbf{x}\|_1, \quad (6)$$

where $\mathbf{A} \in \mathbb{R}^{80 \times 100}$ and $\mathbf{b} \in \mathbb{R}^{100}$ are generated by

```

>> randn('seed',315);
>> A=randn(80,100);
>> b=randn(80,1);

```

We can solve the problem using the proximal gradient method implemented in the MATLAB function `prox_gradient`. The model tackled by the proximal gradient method has the form:

$$\min f(\mathbf{x}) + \lambda g(\mathbf{x}),$$

where (in addition to being convex) f is smooth and g is proper and closed. Problem (6) fits the above model with $f(\mathbf{x}) = \frac{1}{2}\|\mathbf{Ax} - \mathbf{b}\|_2^2$, $g(\mathbf{x}) = \|\mathbf{x}\|_1$, $\lambda = 2$. The syntax for `prox_gradient` is

```
[out,fmin,parout] = prox_gradient(Ffun,Ffun_grad,Gfun,Gfun_prox,lambda,
    startx,[par])
```

To solve the problem using `prox_gradient`, we use the fact that $\nabla f(\mathbf{x}) = \mathbf{A}^T(\mathbf{Ax} - \mathbf{b})$. Invoking `prox_gradient` with 100 iterations starting from the zeros vector yields the following output:

```
>> clear par
>> par.max_iter=100;
>> [out,fmin,parout_pg] =prox_gradient(@(x)0.5*norm(A*x-b,2)^2,...
    @(x)A'*(A*x-b),@(x)norm(x,1),@(x,a)prox_l1(x,a),2,zeros(100,1),par);
*****
prox_gradient
*****
#iter      fun. val.      L val.
   1         44.647100      256.000000
   2         23.720870      256.000000
   3         20.469023      256.000000
   :           :           :
  98         14.989947      256.000000
  99         14.989876      256.000000
 100         14.989808      256.000000
-----
Optimal value =          14.989744
```

The proximal gradient method uses a backtracking procedure to find the stepsize at each iteration. The stepsize at iteration k is given by $1/L_k$ where L_k is a certain ‘Lipschitz estimate’. Note that in the above run, all the Lipschitz estimates were chosen as 256, meaning that the backtracking procedure had an effect only at the first iteration (in which the default initial Lipschitz estimate 1 was increased to 256).

FISTA (implemented in the MATLAB function `fista`), which belongs to the third group of solvers, is a better method than the proximal gradient method in the sense that it possesses an improved worst-case $O(1/k^2)$ rate of convergence in contrast to the $O(1/k)$ rate of the proximal gradient method. The syntax of `fista` is the same as the one of `prox_gradient`. Running 100 iterations of FISTA results with a better function value:

```
>> [out,fmin,parout_fista] =fista(@(x)0.5*norm(A*x-b,2)^2,...
    @(x)A'*(A*x-b),@(x)norm(x,1),@(x,a)prox_l1(x,a),2,zeros(100,1),par);
*****
FISTA
*****
#iter      fun. val.      L val.
   1         23.720870      256.000000
   2         20.469023      256.000000
   3         18.708294      256.000000
   :           :           :
  99         14.988551      256.000000
 100         14.988550      256.000000
-----
Optimal value =          14.988550
```

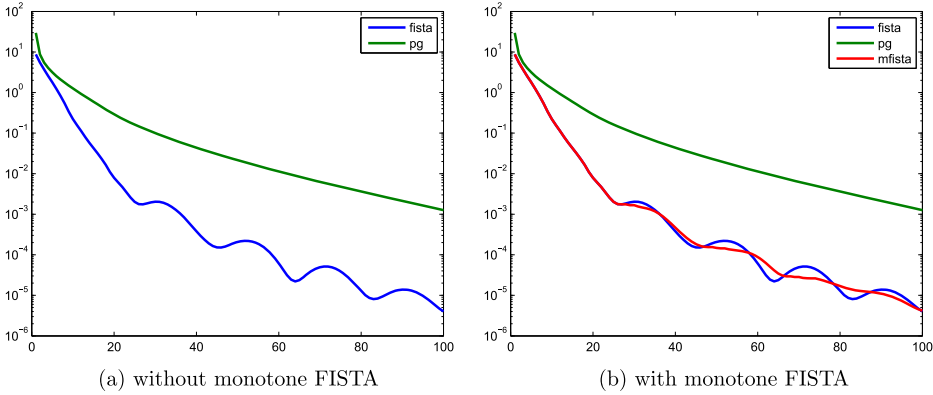


Figure 2. Comparison between proximal gradient, FISTA and monotone FISTA: (a) without monotone FISTA and (b) with monotone FISTA.

To make a more detailed comparison between the two methods, we plot the distance to optimality in terms of function values of the sequences generated by the two methods. The optimal value is approximated by 10,000 iterations of FISTA.

```
>> clear par;
>> par.max_iter=10000;
>> [out,fmin_accurate]=fista(@(x)0.5*norm(A*x-b,2)^2,@(x)A'*(A*x-b),...
    @(x)norm(x,1),@(x,a)prox_l1(x,a),2,zeros(100,1),par);
>> semilogy(1:100,parout_fista.funValVec-fmin_accurate,...
    1:100, parout_pg.funValVec-fmin_accurate,'LineWidth',2);
>> legend('fista','pg')
```

The plot containing the comparison between the two methods is given in Figure 2(a).

As can be clearly seen in Figure 2(a), FISTA is not a monotone method. If one wishes the method to produce a non-increasing sequence of function values, then it is possible to invoke the monotone version of FISTA by setting `par.monotone_flag` to `true`. We can also prevent any screen output by setting `par.print_flag` to `false`. The resulting plot is shown in Figure 2(b).

```
par.max_iter=100;
par.monotone_flag=true;
par.print_flag=false;
[out,fmin,parout_mfista] =fista(@(x)0.5*norm(A*x-b,2),...
    @(x)A'*(A*x-b),@(x)norm(x,1),@(x,a)prox_l1(x,a),2,zeros(100,1),par);
figure(2)
semilogy(1:100,parout_fista.funValVec-fmin_accurate,1:100,...
parout_pg.funValVec-fmin_accurate,1:100,parout_mfista.funValVec-...
fmin_accurate,'LineWidth',2);
legend('fista','pg','mfista');
```

3.5 Non-convexity

Although the solvers in the FOM package require the input function to be convex, they will not prevent the user from inserting non-convex functions and no error message will be returned (like in CVX [13] for example). In cases where the input function is supposed to be smooth and convex, it is possible to plugin a smooth and *non-convex* function, and the solver should work, but instead of guaranteeing convergence to an optimal solution, it is only guaranteed that the limit points of the generated method are stationary points. As an example, consider the problem

$$\min_{\mathbf{x} \in \mathbb{R}^3} \{\mathbf{x}^T \mathbf{A} \mathbf{x} : \|\mathbf{x}\|_2 \leq 1\}, \quad (7)$$

where

```
>> A=[1,1,4;1,1,4;4,4,-2];
```

A is not positive semidefinite, and thus the problem is non-convex. It is easy to see that the stationary points of the problem are the eigenvector corresponding to the minimum eigenvalue -6 and the zeros vector, the former being the actual optimal solution. Problem (7) fits the model

$$\min f(\mathbf{x}) + \lambda g(\mathbf{x})$$

with $f(\mathbf{x}) = \mathbf{x}^T A \mathbf{x}$, $\lambda = 1$ and $g(\mathbf{x}) = \delta_C(\mathbf{x})$, where $C = \{ \mathbf{x} \in \mathbb{R}^3 : \|\mathbf{x}\|_2 \leq 1 \}$. Invoking the proximal gradient method with starting point $(0, -1, 0)^T$ actually results with the optimal solution

```
>> out =prox_gradient(@(x)x'*A*x,@(x)2*A*x,@(x)0,...
    @(x,a)proj_Euclidean_ball(x),1,[0;-1;0]);
*****
prox_gradient
*****
#iter      fun. val.      L val.
   1         1.000000      8.000000
   2        -3.538462      8.000000
   3        -5.537778      8.000000
   :           :           :
  12        -6.000000      8.000000
  13        -6.000000      8.000000
  14        -6.000000      8.000000
Stopping because the norm of the difference between consecutive
iterates is too small
-----
Optimal value =          -6.000000
>> out
out =
    -0.4082
    -0.4083
    0.8165
```

Note that the function handle for g is the zeros function, which has the correct value of g on its domain. In general, when inputting a function handle representing an extended real-valued function to one of the FOM solvers, it is only important that it will be consistent with the function over its domain.

Starting from $(1, 1, 1)^T$ produces the zeros vector which is just a stationary point.

```
>> out =prox_gradient(@(x)x'*A*x,@(x)2*A*x,@(x)0,...
    @(x,a)proj_Euclidean_ball(x),1,[1;1;1]);
*****
prox_gradient
*****
#iter      fun. val.      L val.
   1         6.000000     16.000000
   2         0.375000     16.000000
   3         0.023437     16.000000
   8         0.000000     16.000000
   9         0.000000     16.000000
  10         0.000000     16.000000
Stopping because the norm of the difference between consecutive
iterates is too small
-----
Optimal value =          0.000000
>> out
out =
    1.0e-06 *
    0.5506
    0.5506
    0.5506
```

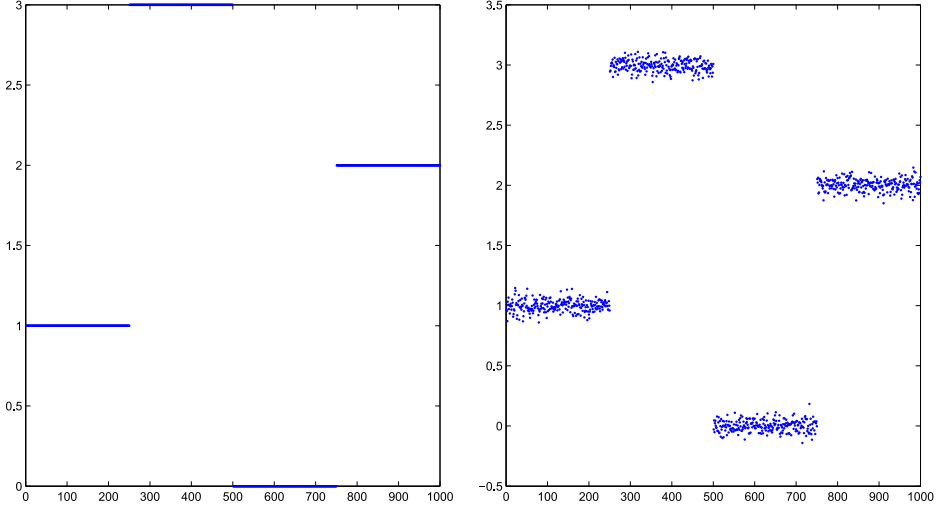



Figure 3. True and noisy step functions.

3.6 One-dimensional signal denoising

Consider the following denoising problem:

$$\min_{\mathbf{x} \in \mathbb{R}^{1000}} \left\{ \frac{1}{2} (x_i - y_i)^2 + 4 \sum_{i=1}^{999} |x_i - x_{i+1}| \right\}, \quad (8)$$

where \mathbf{y} is a noisy step function generated as follows (\mathbf{x} being the original step function):

```
>> randn('seed', 314);
>> x=zeros(1000,1);
>> x(1:250)=1;
>> x(251:500)=3;
>> x(751:1000)=2;
>> y=x+0.05*randn(size(x));
```

We can plot ‘true’ and noisy signals (see Figure 3).

```
>> figure(3)
>> subplot(1,2,1)
>> plot(1:1000,x, '. ')
>> subplot(1,2,2)
>> plot(1:1000,y, '. ')
```

The problem can be solved using the fast dual proximal gradient (FDPG) method implemented in the MATLAB function `fdpg`. The model tackled by the FDPG method is (see Table 1)

$$\min_{\mathbf{x}} f(\mathbf{x}) + \lambda g(\mathcal{A}\mathbf{x}),$$

where f is strongly convex, $\lambda > 0$, \mathcal{A} is a linear transformation and g is proper closed convex and proximal. The denoising problem (8) fits the above model with $\lambda = 4$, $f(\mathbf{x}) = \frac{1}{2} \|\mathbf{x} - \mathbf{y}\|^2$, $g(\mathbf{y}) = \|\mathbf{y}\|_1$ and $\mathcal{A} : \mathbb{R}^{1000} \rightarrow \mathbb{R}^{999}$ being the linear transformation for which $(\mathcal{A}\mathbf{x})_i = x_i - x_{i+1}$, $i = 1, 2, \dots, 999$.

```
A=sparse(999,1000);
A=spdiags([ones(999,1), -ones(999,1)], [0,1], A);
```

The syntax of `fdpg` is

```
[out,fmin,parout] = fdpg(Ffun,F_grad_conj,Gfun,Gfun_prox,Afun,
    Atfun,lambda,starty,[par])
```

The second input argument of `fdpg` is the gradient of f^* , which in this case is given by

$$\nabla f^*(\mathbf{x}) = \underset{\mathbf{z}}{\operatorname{argmax}} \{ \langle \mathbf{x}, \mathbf{z} \rangle - f(\mathbf{z}) \} = \underset{\mathbf{z}}{\operatorname{argmax}} \left\{ \langle \mathbf{x}, \mathbf{z} \rangle - \frac{1}{2} \|\mathbf{z} - \mathbf{y}\|^2 \right\} = \mathbf{x} + \mathbf{y}.$$

The following command computes an optimal solution of (12) using `fdpg`

```
>> [out,fmin,parout] = fdpg(@(x)0.5*norm(x-y)^2,@(x)x+y,...
    @(x)norm(x,1),@(x,a)prox_l1(x,a),@(x)A*x, @(x)A'*x,4,zeros(999,1));
*****
fdpg
*****
#iter      fun. val.      feas. viol.      L val.
    1         248.511179      3.1607e-07      4.000000
    2         107.310785      3.1607e-07      4.000000
    3          74.301824      3.1607e-07      4.000000
    :
   998         28.904498      3.14599e-07      4.000000
   999         28.899496      3.13701e-07      4.000000
  1000         28.895505      3.13267e-07      4.000000
-----
Optimal value =          28.895505
```

It is interesting to note that it is not really necessary to explicitly form the matrix associated with the linear mapping \mathcal{A} , and instead the linear operator and its adjoint can be expressed directly as `@(x)diff(x)` and `@(x)[-x(1);-diff(x);x(end)]` respectively.³

Since the function g is real-valued, it is better to invoke the solver with `par.real_valued_flag` set to `true`, since in this case there is no need to check for feasibility violation and the algorithm outputs the iterate with the smallest function value.

```
>> clear par
>> par.real_valued_flag=true;
>> [out,fmin,parout] = fdpg(@(x)0.5*norm(x-y)^2,@(x)x+y,...
    @(x)norm(x,1),@(x,a)prox_l1(x,a),@(x)A*x, @(x)A'*x,4,zeros(999,1),par);
*****
fdpg
*****
#iter      fun. val.      L val.
    2         107.310785      4.000000
    3          74.301824      4.000000
    4         60.396805      4.000000
    :
   498         28.910757      4.000000
   499         28.899488      4.000000
   500         28.892469      4.000000
-----
Optimal value =          28.892469
```

The last recorded iteration is 500 since there was no improvement of function value following that iteration (although 1000 iterations were employed). Note also that a slightly smaller function value was obtained in this case. The obtained solution is an excellent reconstruction of the original signal (see Figure 4)

```
>> figure(4);
>> plot(1:1000,out,',' )
```

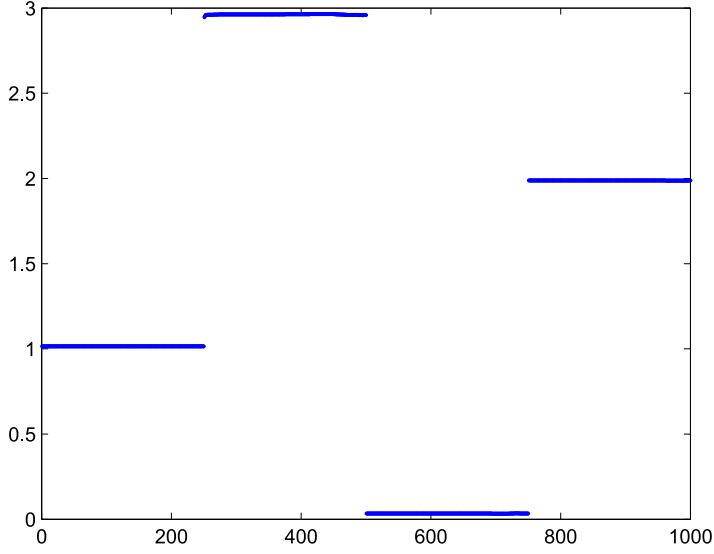


Figure 4. Reconstructed signal using fdpg.

4. Matrix variables

With the exception of `nested_fista`, all the solvers in the FOM package are able to solve problems with matrix variables and are not restricted to solve problems over column vectors. For example, consider the problem

$$\min_{\mathbf{X} \in \mathbb{R}^{30 \times 40}} \left\{ \frac{1}{2} \|\mathbf{C} \odot (\mathbf{X} - \mathbf{D})\|_F^2 + \|\mathbf{AXB}\|_F \right\},$$

where \odot denotes the Hadamard product (that is component-wise product) and $\mathbf{C}, \mathbf{D} \in \mathbb{R}^{30 \times 30}$, $\mathbf{A} \in \mathbb{R}^{20 \times 30}$ and $\mathbf{B} \in \mathbb{R}^{40 \times 50}$ are generated by the commands

```
>> randn('seed', 314);
>> rand('seed', 314);
>> A=randn(20,30);
>> B=randn(40,50);
>> C=1+rand(30,40);
>> D=randn(30,40);
```

To solve the problem, we will use the FDPG method with

$$f(\mathbf{X}) = \|\mathbf{C} \odot (\mathbf{X} - \mathbf{D})\|_F^2, \quad g(\mathbf{Y}) = \|\mathbf{Y}\|_F, \quad \lambda = 1, \quad \mathcal{A}(\mathbf{X}) \equiv \mathbf{AXB}.$$

Note that since \mathbf{C} has only non-zero components, f is strongly convex as required. In employing the FDPG method, we will use the following facts:

- the adjoint linear transformation is given by $\mathbf{X} \mapsto \mathbf{A}^T \mathbf{X} \mathbf{B}^T$,
- the gradient of the conjugate of f is given by $\nabla f^*(\mathbf{Y}) = \operatorname{argmax}_{\mathbf{X}} \{\langle \mathbf{X}, \mathbf{Y} \rangle - f(\mathbf{X})\} = \mathbf{E} \odot \mathbf{Y} + \mathbf{D}$,

where \mathbf{E} is the matrix defined by $E_{ij} = 1/C_{ij}^2$, $i = 1, 2, \dots, 30, j = 1, 2, \dots, 40$.

The command invoking `fdpg` is

```
>> E = 1./(C.^2);
>> clear par
```

```

>> par.real_valued_flag=true;
>> [out,fmin,parout] = fdpg(@(X)0.5*norm(C.*(X-D), 'fro')^2,@(X)E.*X+D,...
    @(X)norm(X, 'fro'),@(x,a)prox_Euclidean_norm(x,a),@(X)A*X*B,...
    @(X)A'*X*B',1,zeros(20,50),par);
*****
fdpg
*****
#iter      fun. val.      L val.
    2         693.740808      4096.000000
    3         623.515605      4096.000000
    6         553.714050      8192.000000
    :           :           :
  281         485.921545      8192.000000
  282         485.921545      8192.000000
  283         485.921545      8192.000000
Stopping because the norm of the difference between consecutive
iterates is too small
-----
Optimal value =          485.921545

```

5. Nested FISTA example – finding a point in the intersection of balls

Consider the problem of finding a point in the intersection of 5000 balls of dimension 200

$$\|\mathbf{x} - \mathbf{c}_i\| \leq r_i, \quad i = 1, 2, \dots, 5000,$$

where the centres and radii are generated by the commands

```

>> randn('seed',315);
>> rand('seed',315);
>> n=200;
>> m=5000;
>> x_true=randn(n,1);
>> r_all=[];
>> c_all=[];
>> for k=1:m
>>     r=rand;
>>     r_all=[r_all;r];
>>     d=randn(n,1);
>>     d=d/norm(d);
>>     c=x_true+0.9*r*d;
>>     c_all=[c_all,c];
>> end

```

The above process starts by choosing randomly a point \mathbf{x}_{true} and then generates 5000 balls that are guaranteed to contain \mathbf{x}_{true} . To solve the problem, we first formulate it as the following minimization problem:

$$\min_{\mathbf{x} \in \mathbb{R}^{200}} \sum_{i=1}^{5000} [\|\mathbf{x} - \mathbf{c}_i\|_2^2 - r_i^2]_+. \quad (9)$$

To solve the problem, we will use the nested FISTA method, which is a simple generalization of FISTA aimed at solving problems of the form (see Table 1 and [Appendix](#) for a detailed description)

$$\min_{\mathbf{x}} \varphi(\mathbf{f}(\mathbf{x})) + g(\mathcal{A}\mathbf{x}), \quad (10)$$

where (in addition to convexity of all the functions involved) φ is a Lipschitz continuous and (componentwise) non-decreasing function, \mathbf{f} is a vector-valued functions whose components are

smooth, \mathcal{A} is a linear transformation and g is proper and closed. Problem (9) fits model (9) with (the choice below of \mathcal{A} is actually arbitrary)

$$\varphi(\mathbf{y}) = \sum_{i=1}^{5000} [y_i]_+, \mathbf{f}(\mathbf{x}) = \begin{pmatrix} \|\mathbf{x} - \mathbf{c}_1\|^2 - r_1^2 \\ \|\mathbf{x} - \mathbf{c}_2\|^2 - r_2^2 \\ \vdots \\ \|\mathbf{x} - \mathbf{c}_{5000}\|^2 - r_{5000}^2 \end{pmatrix}, \quad g(\mathbf{x}) \equiv 0, \mathcal{A} = \mathcal{I}.$$

The syntax of `nested_fista` is

```
[out, fmin, parout] = nested_fista(Phifun, Phifun_prox, Ffun, Ffun_grad, Gfun,
    Gfun_prox, Afun, Atfun, lambda, startx, [par])
```

To solve the problem using `nested_fista`, we will exploit the following formulas (where the prox of $\alpha\varphi$ utilizes the relation $\alpha[u]_+ = (\alpha/2)|u| + \alpha u/2$):

$$\text{prox}_{\alpha\varphi}(\mathbf{y}) = \mathcal{T}_{\frac{\alpha}{2}}\left(\mathbf{y} - \frac{\alpha}{2}\mathbf{e}\right), \quad \nabla f(\mathbf{x}) = 2(\mathbf{x} - \mathbf{c}_1 \quad \mathbf{x} - \mathbf{c}_2 \quad \cdots \quad \mathbf{x} - \mathbf{c}_{5000}),$$

where \mathcal{T}_β is the soft-thresholding operator (also implemented in the MATLAB function `prox_l1`) and \mathbf{e} is the vector of all ones. With the above formulas in mind, we can define

```
>> phi=@(y) sum(pos(y));
>> prox_phi=@(x,a)prox_l1(x-a/2,a/2);
>> f=@(x) (sum_square(x*ones(1,m)-c_all)-(r_all.^2)')';
>> grad_f=@(x) 2*(x*ones(1,m)-c_all);
```

We can now solve the problem

```
>> [xf, fun_xf, parout] = nested_fista (@(x) phi(x), ...
    @(x,a) prox_phi(x,a), @(x) f(x), @(x) grad_f(x), @(x) 0, @(x,a)x, ...
    @(x) x, @(x) x, 1, zeros(n,1));
*****
nested-fista
*****
#iter    fun. val.          L val. inner L val. inner  iternu.
    1      283431.366571   16384.000000      256          50
    2      71260.317218   16384.000000      128          50
    3      9347.554536    16384.000000       64          50
    :          :          :          :          :
   991          0.000000    16384.000000  2.842171e-14      2
   992          0.000000    16384.000000  2.842171e-14      2
   993          0.000000    16384.000000  5.684342e-14      2
Stopping because of 100 iterations with no improvement
-----
Optimal value =          0.000000
```

The obtained solution is a good reconstruction of the vector `x_true`

```
>> norm(x_true-xf)
ans =
    3.6669e-04
```

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Notes

1. This definition of strong convexity is valid since the underlying space is assumed to be Euclidean.
2. For a problem of the form $f_{\text{opt}} = \min\{f(\mathbf{x}) : \mathbf{x} \in X\}$, an ε -optimal solution is a vector $\hat{\mathbf{x}} \in X$ satisfying $f(\hat{\mathbf{x}}) - f_{\text{opt}} \leq \varepsilon$. For a problem of the form $f_{\text{opt}} = \min\{f(\mathbf{x}) : \mathbf{g}(\mathbf{x}) = \mathbf{0}, \mathbf{x} \in X\}$ an ε -optimal and feasible solution is a vector $\hat{\mathbf{x}} \in X$ satisfying $\|\mathbf{g}(\hat{\mathbf{x}})\|_2 \leq \varepsilon, f(\hat{\mathbf{x}}) - f_{\text{opt}} \leq \varepsilon$.
3. We thank an anonymous referee for this observation.

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Appendix. Nested FISTA

Nested FISTA is an extension of the monotone version of FISTA for solving models of the form

$$\min_{\mathbf{x}} \{\varphi(\mathbf{f}(\mathbf{x})) + \lambda g(\mathcal{A}\mathbf{x})\},$$

where

- $\varphi : \mathbb{R}^m \rightarrow \mathbb{R}$ is Lipschitz, non-decreasing and proximable.
- $\mathbf{f} = (f_1, f_2, \dots, f_m)^T : \mathbb{R}^n \rightarrow \mathbb{R}^m$. The components f_1, f_2, \dots, f_m are smooth.
- g – proper closed and proximable.
- \mathcal{A} – linear transformation.
- λ – positive scalar.

The general update formula of nested FISTA is as follows:

- $\mathbf{z}^k = \arg\min_{\mathbf{x} \in \mathbb{R}^n} \{\varphi(\mathbf{f}(\mathbf{y}^k)) + \nabla \mathbf{f}(\mathbf{y}^k)^T (\mathbf{x} - \mathbf{y}^k) + \lambda g(\mathcal{A}\mathbf{x}) + \frac{M_k}{2} \|\mathbf{x} - \mathbf{y}^k\|^2\};$

- $\mathbf{x}^{k+1} \in \operatorname{argmin}_{\mathbf{x} \in \mathbb{R}^n} \{\varphi(\mathbf{f}(\mathbf{x})) + \lambda g(\mathcal{A}\mathbf{x}) : \mathbf{x} \in \{\mathbf{x}^k, \mathbf{z}^k\}\};$
- $t_{k+1} = \frac{1 + \sqrt{1 + 4t_k^2}}{2};$
- $\mathbf{y}^{k+1} = \mathbf{x}^{k+1} + \frac{t_k}{t_{k+1}}(\mathbf{z}^k - \mathbf{x}^{k+1}) + (\frac{t_k - 1}{t_{k+1}})(\mathbf{x}^{k+1} - \mathbf{x}^k).$

The scalar $M_k > 0$ is chosen by a backtracking procedure. The vector \mathbf{z}^k is a solution of an optimization problem that is solved by the FDPG method.