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How to make sure the iterates of “FISTA” converge.

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Introduction

Let \mathcal{H} be an Hilbert space and f and g two convex, l.s.c functions from \mathcal{H} to \mathbb{R} such that f is differentiable with L -Lipschitz continuous gradient, and g is “simple”, meaning that its “proximal map”

$$x \mapsto \arg \min_{y \in \mathcal{H}} g(y) + \frac{\|x - y\|^2}{2\tau}$$

can be easily computed.

We consider the following minimization problem

$$\min_{x \in \mathcal{H}} F(x) := f(x) + g(x) \tag{1}$$

and we assume that this problem has at least a solution (and possibly an infinite set of solutions).

Among the many algorithms which exist to tackle such problems, the proximal splitting algorithms, which perform alternating descents in f and in g , are frequently used, because of their simplicity and relatively small per-iteration complexity. One can mention the Forward-Backward (FB) splitting, the Douglas-Rachford splitting, the ADMM (alternating direction method of multipliers),¹ which all have been proved to be efficient in many imaging problem such as denoising, inpainting, deconvolution, color transfert and many others.

This work focuses on the so-called “Fast Iterative Soft Thresholding Algorithm” (FISTA) which is an accelerated variant of the Forward-Backward algorithm proposed by Beck and Teboulle [2], built upon ideas of Nesterov [11] and Güler [7].

¹See for instance [4, 8, 5, 6, 3].

The FB is a descent algorithm which defines a sequence $(x_n)_{n \in \mathbb{N}}$ by performing an explicit descent in f and implicit in g . It is then shown that there exist $C > 0$, such that for all $n \in \mathbb{N}$ $F(x_n) - F(x^*) \leq \frac{C}{n}$ where x^* is a minimizer of F . Moreover the sequence $(x_n)_{n \in \mathbb{N}}$ weakly converges in \mathcal{H} . See for instance [13] or [2] for a simple derivation of this rate.

The sequence $(x_n)_{n \in \mathbb{N}}$ defined by the accelerated variant ‘‘FISTA’’ [2] satisfies, on the other hand, $F(x_n) - F(x^*) \leq \frac{C'}{n^2}$ for a suitable real number C' , however no convergence of $(x_n)_{n \in \mathbb{N}}$ as been proved so far.

The FISTA algorithm is based on a simple over-relaxation step with varying parameter, and several choices of parameters yield roughly the same rate of convergence. This paper provides complementary results on the convergence of $F(x_n) - F(x^*)$ for some ‘‘good’’ choices of these parameters, for which the weak convergence of the iterates can also be proved.

In the next section, we introduce a few definitions and our main notation. In a second part, the main result on the convergence of FISTA is recalled, and we give new results on the convergence of the values of $F(x_n)$, for other over-relaxation sequences. In the third part we show the convergence of the iterates. This part is strongly inspired from a recent paper of Pock and Lorenz [9], inspired by works of Alvarez and Attouch [1]. The last part is focused on numerical experiments.

1 Notation and definitions

In the following x^* denotes a solution of (1), even if this solution is not unique the value $F(x^*)$ is uniquely defined.

A key tool of FISTA is the proximal map. To any proper, convex and l.s.c function h is associated the proximal map Prox_h which is a function from \mathcal{H} to \mathcal{H} defined by

$$\text{Prox}_h(x) = \arg \min_{y \in \mathcal{H}} h(y) + \frac{1}{2} \|x - y\|^2.$$

This function is uniquely defined and generalizes the projection on a closed convex set to convex functions.

In the sequel, γ denotes a non negative real number such that $\gamma \leq \frac{1}{L}$ where L is the Lipschitz constant of ∇f and T the mapping from \mathcal{H} to \mathcal{H} defined by

$$T(x) := \text{Prox}_{\gamma g}(x - \gamma \nabla f(x)),$$

The idea of FB is to apply this mapping from any $x_0 \in \mathcal{H}$ using Krasnosel’ski Mann iterations to get a weak convergence to a minimizer x^* of F . The idea of FISTA is to apply this mapping using a suitable extragradient rule to accelerate the convergence.

FISTA is defined by a sequence $(t_n)_{n \in \mathbb{N}}$ of real numbers greater than 1 and a point $x_0 \in \mathcal{H}$. Let $(t_n)_{n \in \mathbb{N}^*}$ be a sequence of non negative real numbers and $x_0 \in \mathcal{H}$, the sequences $(x_n)_{n \in \mathbb{N}}$, $(y_n)_{n \in \mathbb{N}}$ and $(u_n)_{n \in \mathbb{N}}$ and $(y_n)_{n \in \mathbb{N}}$ are defined by $y_0 = u_0 = x_0$ and for all $n \geq 1$,

$$x_n = T(y_{n-1}) \quad (2)$$

$$y_n = \left(1 - \frac{1}{t_{n+1}}\right) x_n + \frac{1}{t_{n+1}} u_n \quad (3)$$

$$u_n = x_{n-1} + t_n(x_n - x_{n-1}). \quad (4)$$

The point y_n may also be defined from points x_n and x_{n-1} by

$$y_n = x_n + \alpha_n(x_n - x_{n-1}) \text{ with } \alpha_n := \frac{t_n - 1}{t_{n+1}} \quad (5)$$

For suitable choices of $(t_n)_{n \in \mathbb{N}^*}$ the sequence $(F(x_n))_{n \in \mathbb{N}}$ converge to $F(x^*)$, i.e the sequence $(w_n)_{n \in \mathbb{N}}$, defined as follows,

$$w_n := F(x_n) - F(x^*) \quad (6)$$

tends to 0 when n goes to infinity.

Several proofs use bounds on the local variation of the sequence $(x_n)_{n \in \mathbb{N}}$, which we will denote $(\delta_n)_{n \in \mathbb{N}}$: variation :

$$\delta_n := \frac{1}{2} \|x_n - x_{n-1}\|_2^2$$

The sequence $(v_n)_{n \in \mathbb{N}}$ denoting the distance between u_n and a fixed minimizer x^* of F will also be useful:

$$v_n := \frac{1}{2} \|u_n - x^*\|_2^2.$$

To complete this part devoted to our notation, we define a sequence $(\rho_n)_{n \in \mathbb{N}}$, associated to $(t_n)_{n \in \mathbb{N}^*}$, whose positivity will ensure the convergence of the FISTA iterations:

$$\rho_n := t_{n-1}^2 - t_n^2 + t_n.$$

2 Basic and complementary results on FISTA

The main result of [2] is the following Theorem :

Theorem 1 ([2, Thm. 4.1]). *For any $x_0 \in \mathcal{H}$, if the sequence $(t_n)_{n \in \mathbb{N}^*}$ satisfies*

$$\forall n \geq 2 \quad t_n^2 - t_n \leq t_{n-1}^2 \quad (7)$$

and $t_1 = 1$, if $\gamma \leq \frac{1}{L}$ then the sequence $(x_n)_{n \in \mathbb{N}}$ satisfies for all $n \in \mathbb{N}$

$$w_n \leq \frac{1}{2\gamma t_n^2} \|x_0 - x^*\|_2^2 \quad (8)$$

for any minimizer x^* of F .

Condition (7) can also be stated using the sequence $(\rho_n)_{n \in \mathbb{N}}$: $\forall n \geq 2, \rho_n \geq 0$.
The sequence defined by $t_1 = 1$ and

$$\forall n \in \mathbb{N}^* \quad t_{n+1} = \sqrt{t_n^2 + \frac{1}{4}} + \frac{1}{2} \quad (9)$$

achieves the equality in (7). Also, it turns out that the sequence $(t_n)_{n \in \mathbb{N}}$ defined by $t_n = \frac{n+1}{2}$ satisfies condition (7). But more generally, for any $a \geq 2$ the sequence $(t_n)_{n \in \mathbb{N}}$ defined by $t_n = \frac{n+a-1}{a}$ satisfies (7). Indeed,

$$\rho_n = \frac{1}{a^2} ((n+a-2)^2 - (n+a-1)^2 + a(n+a-1)) = \frac{1}{a^2} ((a-2)n + a^2 - 3a + 3) \geq 0. \quad (10)$$

An induction proves that any sequence satisfying (7) (hence an inequality in (9)) and $t_1 = 1$ satisfies $t_n \leq n$. Hence for any sequence defined above, Theorem 1 ensures that

$$\forall n \in \mathbb{N} \quad w_n \leq \frac{C}{n^2} \quad (11)$$

where C depends on the exact choice of the sequence $(t_n)_{n \in \mathbb{N}}$.

A priori, the best constant “ C ” in this bound $\frac{C}{n^2}$ will be reached if the sequence $(t_n)_{n \in \mathbb{N}}$ is the one achieving the equality in (7), given by (9), ensuring the highest value of t_n . This is the choice in [2], and it turns out that it is nearly optimal (since for any n there exists a problem which has lower bound of the same order, see [10, 12]). We will soon see, however, that not achieving this equality may have some advantages.

This first Theorem can easily be made more precise, as follows:

Theorem 2. *If the sequence $(t_n)_{n \in \mathbb{N}}$ satisfies (7) and $t_1 = 1$, if $\gamma \leq \frac{1}{L}$ then for any $N \geq 2$,*

$$t_{N+1}^2 w_{N+1} + \sum_{n=1}^N \rho_{n+1} w_n \leq \frac{v_0 - v_{N+1}}{\gamma}. \quad (12)$$

Using the several choices of sequence $(t_n)_{n \in \mathbb{N}}$ described above, Theorem 2 ensures the same decay for w_n ($w_n \leq \frac{C}{n^2}$) as the previous. But using (10), we readily see that for a “good” choice of the sequence $(t_n)_{n \in \mathbb{N}^*}$, one obtains the following corollary:

Corollary 1. *Let $a > 2$ and for $n \geq 1$, $t_n = \frac{n+a-1}{a}$. Then the sequence $(nw_n)_{n \in \mathbb{N}}$ belongs to $\ell_1(\mathbb{N})$. In particular, $\liminf_{n \rightarrow \infty} n^2 \ln nw_n = 0$.*

The classical choice (9) for the sequence $(t_n)_{n \in \mathbb{N}^*}$ may yield the best rate of convergence for the objective, but other sequences can give better global properties of the sequence $(nw_n)_{n \in \mathbb{N}}$. (Also notice that the other classical choice corresponding to $a = 2$ will not ensure this summability.) An important remark, here, is that this result is not in contradiction with the lower bounds of Nemirovski and Yudin (see [10, 12]). Indeed, they show that for any integer n_0 one can build a specific problem for which one will have, after n_0 iterations, $n_0 w_{n_0} \geq C/n_0$, however this does not mean that the sequence $(nw_n)_n$ is not eventually summable.

Proof of Theorem 2 The proof is similar to the one of Theorem 1 in [2], however for the ease of the reader we will sketch it here. A first (standard) technical descent Lemma is useful:

Lemma 1. *Let $\gamma \in]0, \frac{1}{L}]$, where L is the Lipschitz constant of ∇f , $\bar{x} \in \mathcal{H}$ and $\hat{x} = T\bar{x}$. Then*

$$\forall x \in \mathcal{H} \quad F(\hat{x}) + \frac{\|\hat{x} - x\|^2}{2\gamma} \leq F(x) + \frac{\|x - \bar{x}\|^2}{2\gamma} \quad (13)$$

Proof. Many proofs exist of this result, we give an elementary one which is inspired from [15]. By definition of the proximal map, \hat{x} is the minimizer of the $\frac{1}{\gamma}$ -strongly convex function

$$z \mapsto f(z) + g(\bar{x}) + \langle \nabla g(\bar{x}), z - \bar{x} \rangle + \frac{1}{2\gamma} \|z - \bar{x}\|^2$$

hence for all $z \in \mathcal{H}$

$$\begin{aligned} f(\hat{x}) + g(\bar{x}) + \langle \nabla g(\bar{x}), \hat{x} - \bar{x} \rangle + \frac{\|\bar{x} - \hat{x}\|^2}{2\gamma} + \frac{\|z - \hat{x}\|^2}{2\gamma} \\ \leq f(z) + g(\bar{x}) + \langle \nabla g(\bar{x}), z - \bar{x} \rangle + \frac{\|z - \bar{x}\|^2}{2\gamma}. \end{aligned}$$

Since $\gamma \leq 1/L$, it follows

$$f(\hat{x}) + g(\hat{x}) + \frac{1}{2\gamma} \|z - \hat{x}\|^2 \leq f(z) + g(\bar{x}) + \langle \nabla g(\bar{x}), z - \bar{x} \rangle + \frac{1}{2\gamma} \|z - \bar{x}\|^2.$$

By convexity, $g(\bar{x}) + \langle \nabla g(\bar{x}), z - \bar{x} \rangle \leq g(z)$. We deduce that (13) holds and the Lemma is proved. \square

Proof of Theorem 2. Applying this Lemma to $\bar{x} = y_n$, $\hat{x} = x_{n+1}$ and $x = (1 - \frac{1}{t_{n+1}})x_n + \frac{1}{t_{n+1}}x^*$, we find

$$\begin{aligned} F(x_{n+1}) + \frac{\left\| \frac{1}{t_{n+1}}u_{n+1} - \frac{1}{t_{n+1}}x^* \right\|_2^2}{2\gamma} \\ \leq F\left(\left(1 - \frac{1}{t_{n+1}}\right)x_n + \frac{1}{t_{n+1}}x^*\right) + \frac{\left\| \frac{1}{t_{n+1}}x^* - \frac{1}{t_{n+1}}u_n \right\|_2^2}{2\gamma} \end{aligned}$$

Using the convexity of F it follows

$$\begin{aligned} F(x_{n+1}) - F(x^*) - \left(1 - \frac{1}{t_{n+1}}\right)(F(x_n) - F(x^*)) \\ \leq \frac{\|u_n - x^*\|_2^2}{2\gamma t_{n+1}^2} - \frac{\|u_{n+1} - x^*\|_2^2}{2\gamma t_{n+1}^2} \end{aligned}$$

Using definitions of w_n and v_n this inequality can be stated

$$t_{n+1}^2 w_{n+1} - (t_{n+1}^2 - t_{n+1})w_n \leq \frac{v_n - v_{n+1}}{\gamma} \quad (14)$$

Summing these inequalities from $n = 1$ to $n = N$ leads to

$$t_{N+1}^2 w_{N+1} + \sum_{n=1}^N \rho_{n+1} w_n \leq \frac{v_0 - v_{N+1}}{\gamma}. \quad (15)$$

which ends the proof of Theorem 2. \square

We can deduce another useful corollary:

Corollary 2. *Let $a > 2$ and for $n \geq 1$, $t_n = \frac{n+a-1}{a}$. Then the sequence $(n\delta_n)_{n \in \mathbb{N}}$ belongs to $\ell_1(\mathbb{N})$, in particular $\liminf_{n \rightarrow \infty} n^2 \ln n \delta_n = 0$. In addition, there exists $C > 0$ such that for all $n \in \mathbb{N}^*$, $\delta_n \leq \frac{C}{n^2}$.*

This results which is a consequence of previous corollary is the key to prove the convergence of the sequence $(x_n)_{n \in \mathbb{N}}$.

Proof. Applying Lemma 1 to $\bar{x} = y_n = x_n + \alpha_n(x_n - x_{n-1})$, and $x = x_n$ leads to

$$F(x_{n+1}) + \frac{\|x_n - x_{n+1}\|_2^2}{2\gamma} \leq F(x_n) + \frac{\alpha_n^2 \|x_n - x_{n-1}\|_2^2}{2\gamma}$$

which can be written with definitions of w_n and δ_n

$$\delta_{n+1} - \alpha_n^2 \delta_n \leq \gamma(w_n - w_{n+1})$$

If $t_n = \frac{n+a-1}{a}$, $\alpha_n = \frac{t_n-1}{t_{n+1}} = \frac{n-1}{n+a}$.

Multiplying this inequality by $(n+a)^2$ and adding from $n = 1$ to $n = N$ leads to

$$\sum_{n=1}^N (n+a)^2 (\delta_{n+1} - \alpha_n^2 \delta_n) \leq \gamma \sum_{n=1}^N (n+a)^2 (w_n - w_{n+1}),$$

which gives

$$(N+a)^2 \delta_{N+1} + \sum_{n=2}^N ((n+a-1)^2 - (n+a)^2 \alpha_n^2) \delta_n \leq \gamma \left((a+1)^2 w_1 - (N+a)^2 w_{N+1} + \sum_{n=2}^N ((n+a)^2 - (n+a-1)^2) w_n \right)$$

that is

$$(N+a)^2 \delta_{N+1} + \sum_{n=2}^N a(2n-2+a) \delta_n \leq \gamma \left((a+1)^2 w_1 - (N+a)^2 w_{N+1} + \sum_{n=2}^N (2n+2a-1) w_n \right)$$

By Corollary 1 and since we have assumed $a > 2$, the right part of the inequality is uniformly bounded independently of N , which ensures that the sequence $(n\delta_n)_{n \in \mathbb{N}}$ belongs to $\ell_1(\mathbb{N})$. \square

3 Convergence of the iterates of FISTA

In this section, we show the following Theorem

Theorem 3. *Let $a > 2$ be a positive real number, and for all $n \in \mathbb{N}$ let $t_n = \frac{n+a-1}{a}$. Then the sequence $(x_n)_{n \in \mathbb{N}}$ given by FISTA weakly converges to a minimizer of F .*

The proof of the theorem follows the ideas of Pock and Lorenz, in the proof of Theorem 1 in [9]—see also [1]. The two main differences between our setting and the setting of [9] are:

1. We do not assume the existence of $\alpha < 1$ such that $\forall n \geq 1, \alpha_n \leq \alpha$;

2. The sequence $(\delta_n)_{n \in \mathbb{N}}$ produced by FISTA, with a good choice of the sequence (t_n) , has stronger properties than in [9].

It turns out that Corollary 2 is crucial, while classical bounds on δ_n which only show the existence of a constant $C > 0$ such that $\delta_n \leq \frac{C}{n^2}$ are not sufficient.

Before giving the complete proof of this result, several remarks can be done.

1. From Corollary 2 it follows that the sequence $(n(x_{n+1} - x_n))_{n \in \mathbb{N}}$ is bounded, moreover the sequence $(v_n)_{n \in \mathbb{N}}$ is also bounded which implies that the sequence $((x_n)_{n \in \mathbb{N}})$ is bounded.
2. Hence there exists a subsequence of $((x_n)_{n \in \mathbb{N}})$ that weakly converges to a $\tilde{x} \in \mathcal{H}$, $x_\nu \rightharpoonup \tilde{x}$.
3. Since the sequence $(\delta_n)_{n \in \mathbb{N}}$ tends to 0, $y_\nu \rightharpoonup \tilde{x}$ which implies that \tilde{x} is a fixed point of the non expansive operator T , hence a minimizer of F .

If we are able to prove that the sequence $\|x_n - x^*\|$ has a limit for any minimizer x^* of F , Theorem 3 will follow, taking for x^* the weak limit \tilde{x} of our subsequence and invoking Opial's Theorem [14].

Proof of Theorem 3. Let us define for all $j \geq 1$ and for all $k \geq j$

$$\beta_{j,k} = \prod_{l=j}^k \alpha_l = \prod_{l=j}^k \frac{l-1}{l+a}.$$

and $\beta_{j,k} = 1$ if $j > k$.

Since $\alpha_1 = 0$, $\forall k > 1$, $\beta_{1,k} = 0$. Moreover since $a > 2$,

$$\beta_{j,k} \leq \prod_{l=j}^k \frac{l-1}{l+2}.$$

Hence, for all $j \geq 2$ and for all $k \geq 1$, $\beta_{j,k} \leq 1$, while if $k - j \geq 2$,

$$\beta_{j,k} \leq \left(\frac{j+1}{k} \right)^3.$$

It follows that for all $j \geq 2$,

$$\begin{aligned} \sum_{k=j}^{+\infty} \beta_{j,k} &\leq 2 + \sum_{k=j+2}^{+\infty} \beta_{j,k} \leq 2 + \sum_{k=j+2}^{+\infty} \left(\frac{j+1}{k} \right)^3 \leq 2 + (j+1)^3 \sum_{k=j+2}^{+\infty} \frac{1}{k^3} \\ &\leq 2 + (j+1)^3 \int_{t=j+1}^{+\infty} \frac{dt}{t^3} \leq 2 + (j+1)^3 \frac{1}{2(j+1)^2} \end{aligned}$$

and then

$$\sum_{k=j}^{+\infty} \beta_{j+1,k} \leq \frac{j+5}{2}. \quad (16)$$

Let us define

$$\Phi_n = \frac{1}{2} \|x_n - x^*\|_2^2 \quad \text{and} \quad \Gamma_n = \frac{1}{2} \|x_{n+1} - y_n\|_2^2$$

From the identity

$$\langle a - b, a - c \rangle = \frac{1}{2} \|a - b\|_2^2 + \frac{1}{2} \|a - c\|_2^2 - \frac{1}{2} \|b - c\|_2^2 \quad (17)$$

we have by using the definition of y_n

$$\Phi_n - \Phi_{n+1} = \delta_{n+1} + \langle y_n - x_{n+1}, x_{n+1} - x^* \rangle - \alpha_n \langle x_n - x_{n-1}, x_{n+1} - x^* \rangle \quad (18)$$

Then, using the monotonicity of ∂g , we deduce that for any $z_{n+1} \in \partial g(x_{n+1})$ and for any $z^* \in \partial g(x^*)$

$$\langle \gamma z_{n+1} - \gamma z^*, x_{n+1} - x^* \rangle \geq 0$$

By definition of x^* , $-\nabla(f(x^*)) \in \partial g(x^*)$ and $y_n - x_{n+1} - \gamma \nabla f(y_n) \in \gamma \partial g(x_{n+1})$.

It follows

$$\begin{aligned} \langle y_n - x_{n+1} - \gamma \nabla f(y_n) + \gamma \nabla f(x^*), x_{n+1} - x^* \rangle &\geq 0 \\ \langle y_n - x_{n+1}, x_{n+1} - x^* \rangle + \gamma \langle \nabla f(x^*) - \nabla f(y_n), x_{n+1} - x^* \rangle &\geq 0 \end{aligned}$$

Combining with (18) we obtain

$$\Phi_n - \Phi_{n+1} \geq \delta_{n+1} + \gamma \langle \nabla f(y_n) - \nabla f(x^*), x_{n+1} - x^* \rangle - \alpha_n \langle x_n - x_{n-1}, x_{n+1} - x^* \rangle. \quad (19)$$

From the co-coercivity of ∇f , we have

$$\begin{aligned} \langle \nabla f(y_n) - \nabla f(x^*), x_{n+1} - x^* \rangle &= \langle \nabla f(y_n) - \nabla f(x^*), x_{n+1} - y_n + y_n - x^* \rangle \\ &\geq \frac{1}{L} \|\nabla f(y_n) - \nabla f(x^*)\|_2^2 + \langle \nabla f(y_n) - \nabla f(x^*), x_{n+1} - y_n \rangle \\ &\geq \frac{1}{L} \|\nabla f(y_n) - \nabla f(x^*)\|_2^2 - \frac{1}{L} \|\nabla f(y_n) - \nabla f(x^*)\|_2^2 - \frac{L}{2} \Gamma_n \\ &\geq -\frac{L}{2} \Gamma_n. \end{aligned}$$

Substituting back into (19), we get

$$\Phi_n - \Phi_{n+1} \geq \delta_{n+1} - \frac{\gamma L}{2} \Gamma_n - \alpha_n \langle x_n - x_{n-1}, x_{n+1} - x^* \rangle,$$

and invoking (17) it follows that

$$\begin{aligned}\Phi_{n+1} - \Phi_n - \alpha_n(\Phi_n - \Phi_{n-1}) &\leq -\delta_{n+1} + \frac{\gamma L}{2}\Gamma_n \\ &\quad + \alpha_n(\delta_n + \langle x_n - x_{n-1}, x_{n+1} - x_n \rangle) \\ &= -\Gamma_n + \frac{\gamma L}{2}\Gamma_n + (\alpha_n + \alpha_n^2)\delta_n,\end{aligned}$$

where we have used the fact that

$$\delta_{n+1} - \alpha_n \langle x_n - x_{n-1}, x_{n+1} - x_n \rangle = \alpha_n^2 \frac{\|x_n - x_{n-1}\|^2}{2} - \frac{\|x_{n+1} - y_n\|^2}{2}.$$

Using $\frac{\alpha_n + \alpha_n^2}{2} \leq \alpha_n$ we obtain

$$\Phi_{n+1} - \Phi_n - \alpha_n(\Phi_n - \Phi_{n-1}) \leq -\left(1 - \frac{\gamma L}{2}\right)\Gamma_n + 2\alpha_n\delta_n \quad (20)$$

with $1 - \frac{\gamma L}{2} > 0$.

Now defining $\theta_n = \max(0, \Phi_n - \Phi_{n-1})$ we obtain

$$\theta_{n+1} \leq \alpha_n(\theta_n + 2\delta_n) \quad (21)$$

Applying recursively (21) it follows that for all $n \geq 2$ ($\alpha_1 = 0$, and in particular $\theta_1, \theta_2 = 0$).

$$\theta_{n+1} \leq 2 \sum_{j=2}^n \left(\prod_{l=j}^n \alpha_l \right) \delta_j = 2 \sum_{j=2}^n \beta_{j,n} \delta_j. \quad (22)$$

Hence (using (16)),

$$\begin{aligned}\sum_{n=2}^{+\infty} \theta_n &\leq 2 \sum_{n=1}^{+\infty} \sum_{j=2}^n \beta_{j,n} \delta_j \\ &\leq 2 \sum_{j=2}^{\infty} \delta_j \sum_{n=j}^{\infty} \beta_{j,n} \\ &\leq 2 \sum_{j=1}^{\infty} \delta_j \frac{j+5}{2}.\end{aligned}$$

From Corollary 2 the right side of the last inequality is finite if $a > 2$, therefore the sequence $(\theta_n)_{n \in \mathbb{N}}$ belongs to $\ell_1(\mathbb{N})$.

The end of the proof follows Lorenz and Pock [9]. We set $s_n = \Phi_n - \sum_{i=1}^n \theta_i$ and since $\Phi_n \geq 0$ and $\sum_{i=1}^n \theta_i$ is bounded independently of n , we see that s_n is bounded from below. On the other hand

$$s_{n+1} = \Phi_{n+1} - \theta_n - \sum_{i=1}^n \theta_n \leq \Phi_{n+1} - \Phi_{n+1} + \Phi_n - \sum_{i=1}^n \theta_i = s_n$$

and hence $(s_n)_{n \in \mathbb{N}}$ is a non-decreasing sequence and thus is convergent. This implies that Φ_n is convergent, which concludes the proof of Theorem 3. \square

4 Numerical Experiments

In previous parts, it was shown that non classical choices of the sequence $(t_n)_{n \in \mathbb{N}}$ ensure weak convergence of iterates $(x_n)_{n \in \mathbb{N}}$ and good properties for the sequence $(F(x_n) - F(x^*))_{n \in \mathbb{N}}$. On two examples, inpainting, and deblurring, we compare several choices of parameters.

For each example the 4 following sequences are tested :

- $t_1 = 1$ and $\forall n \in \mathbb{N}, t_{n+1} = \sqrt{t_n^2 + \frac{1}{4}} + \frac{1}{2}$,
- $t_n = \frac{n+a+1}{a}, \forall n \in \mathbb{N}$ with $a = 2, 3$ and 4 .

For each problem, at each iteration n , the values $\|x_n - x_{n-1}\|_2^2$ and $F(x^n) - F(x^*)$ are computed. Since $F(x^*)$ can not be exactly computed, the value $F(x^*)$ is estimated by the minimum of the values computed on 500 iterations for the four methods. The graph of the logarithm of these two quantities is thus given from $n = 1$ to $n = 400$.

Inpainting Let us consider here a degraded image $y^0 = Mx^0$ where x^0 is an unknown source image and M a mask operator. In our example 50% of the pixels are removed. The image x^0 can be estimated from y^0 minimizing

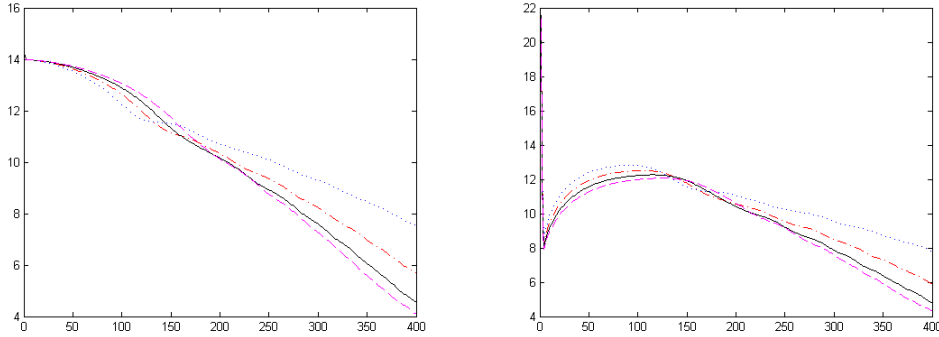
$$F(x) = \frac{1}{2} \|y^0 - Mx\|_2^2 + \lambda \|Tx\|_1 \quad (23)$$

where λ is a small non negative real number and T is an orthogonal (Daubechies) wavelet transform.

Considering $f(x) = \frac{1}{2} \|y^0 - Mx\|_2^2$ and $g(x) = \lambda \|Tx\|_1$, FISTA may be applied to minimize F .



Left: the masked image y^0 . Right: an image \hat{x} estimated minimizing F with FISTA.²



Left: values of $\log(F(x_n) - F(x^*))$. Right: values of $\log(\|x_n - x_{n-1}\|_2^2)$. Blue dot line classical FISTA, red dashed-dot line $a = 2$, black solid line $a = 3$ and magenta dashed line $a = 4$.

On this example, the choices $a = 3$ or $a = 4$ seems better than classical choices after 100 iterations. One can notice that classical FISTA is better for a small number of iterations.

Deblurring In this second example $y^0 = h \star x^0 + n$ is the noisy image of a blurred images x^0 , where h is a gaussian filter and n is a random gaussian noise. The image x^0 can be estimated minimizing

$$F(x) = \frac{1}{2} \|y^0 - h \star x\|_2^2 + \lambda \|Tx\|_1 \quad (24)$$

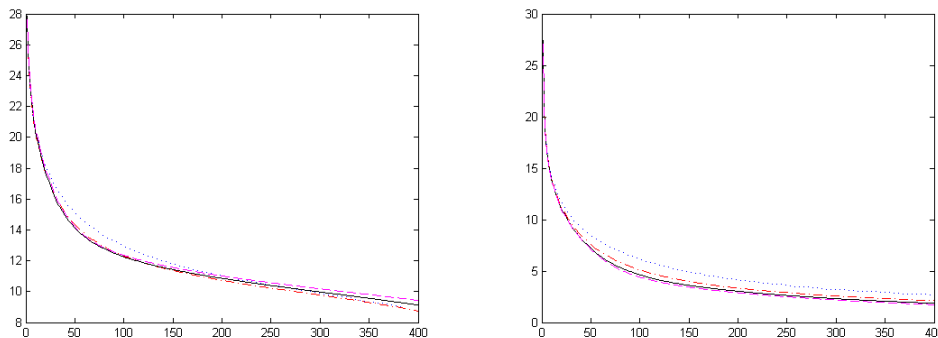
where λ is a small non negative real number which value depends on the noise level and T is an orthogonal (Daubechies) wavelet transform.

²The images provided by the 4 versions of FISTA look very similar, the difference appears in the values of the variation of fonctionnal F through the iterations.

Considering $f(x) = \frac{1}{2} \|y^0 - h \star x\|_2^2$ and $g(x) = \lambda \|Tx\|_1$, FISTA may be applied to minimize F .



Left: the blurred image y^0 . Right: an image \hat{x} estimated minimizing F with FISTA.



Left: values of $\log(F(x_n) - F(x^*))$. Right: values of $\log(\|x_n - x_{n-1}\|_2^2)$. Blue dot line classical FISTA, red dashed-dot line $a = 2$, black solid line $a = 3$ and magenta dashed line $a = 4$.

On this example, the choices the classical FISTA seems better after 200 iterations, but the decreasing of δ_n seems still better for $a = 3$ and $a = 4$.

TV denoising Let us consider now a noisy image $y^0 = x^0 + n$. The image x^0 may be estimated from y^0 minimizing

$$F(x) = \frac{1}{2} \|y^0 - x\|_2^2 + \lambda \|\nabla x\|_1 \quad (25)$$

where ∇x is the gradient of the image x and $\|\nabla x\|_1$ is the isotropic ℓ_1 -norm of the gradient. This regularization is also called Total Variation (TV) regularization. The proximal map of the function $x \mapsto \|\nabla x\|_1$ does not have a close form and

FISTA is difficult to use directly here nevertheless by duality this minimization problem is equivalent to minimize

$$G(p) = \frac{1}{2} \|y^0 + \operatorname{div} p\|_2^2 + i_{\| \cdot \|_\infty \leq \lambda}(p) \quad (26)$$

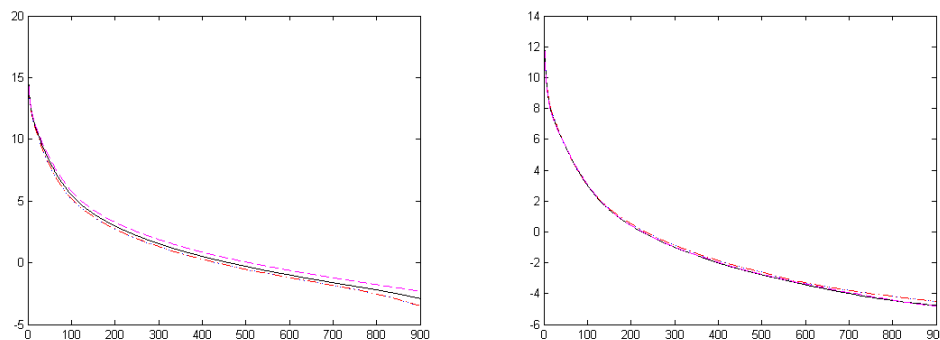
where i_C denotes the function such that $i_C(x) = 0$ if $x \in C$ and $i_C(x) = +\infty$ if $x \notin C$ and where $x \mapsto -\operatorname{div} x$ is the divergence operator, conjugate of the gradient ∇ .

These two problems are equivalent and for any solution p^* of the second minimization problem, $y^0 + \operatorname{div} p^*$ is a solution of the first minimization problem.

This second problem can be solved using FISTA since the gradient of $p \mapsto \frac{1}{2} \|y + \operatorname{div} p\|_2^2$ is Lipschitz and the proximal map of $p \mapsto i_{\| \cdot \|_\infty \leq \lambda}(p)$ is a simple projection.



Left: noisy image y^0 . Right: the image \hat{x} estimated minimizing F with FISTA.



Left: values of $\log(G(p_n) - G(p^*))$. Right: values of $\log(\|p_n - p_{n-1}\|_2^2)$.
 Blue dot line classical FISTA, red dashed-dot line $a = 2$, black solid line $a = 3$
 and magenta dashed line $a = 4$.

These three examples shows that choosing a priori a sequence $(t_n)_{n \in \mathbb{N}}$ for FISTA is difficult and that for a given problem, it would be useful to test various options.

Sometimes the classical parameters proposed by Beck and Teboulle are better to get a faster minimization, sometimes the use of $a = 3$ or $a = 4$ is better. But on the three examples the norm of the variation δ_n is smaller for $a = 3$ or $a = 4$ than $a = 2$ or the classical FISTA, which may indicate that the convergence of the iterates is faster.

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