

# On Landweber-Kaczmarz methods for regularizing systems of ill-posed equations in Banach spaces

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## Abstract

In this article Iterative regularization methods of Landweber-Kaczmarz type are considered for solving systems of ill-posed equations modeled (finitely many) by operators acting between Banach spaces. Using assumptions of uniform convexity and smoothness on the parameter space, we are able to prove a monotony result for the proposed method, as well as to establish convergence (for exact data) and stability results (in the noisy data case). Regularity assumptions on the solution, such as source conditions, are not required in the analysis.

**Keywords.** Nonlinear systems; Banach spaces; Regularization; Landweber iteration, Kaczmarz method.

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## 1 Introduction

### 1.1 Systems of nonlinear ill-posed equations

In this paper we propose a new method for obtaining regularized approximations of systems of nonlinear ill-posed operator equations in Banach spaces.

The *inverse problem* we are interested in consists of determining an unknown physical quantity  $x \in X$  from the set of data  $(y_1, \dots, y_m) \in Y^m$ , where  $X, Y$  are Banach spaces,  $X$  uniformly convex and smooth [6], and  $m \geq 1$ .

In practical situations, we do not know the data exactly. Instead, we have only approximate measured data  $y_i^\delta \in Y$  satisfying

$$\|y_i^\delta - y_i\| \leq \delta_i, \quad i = 1, \dots, m, \quad (1)$$

with  $\delta_i > 0$  (noise level). The finite set of data above is obtained by indirect measurements of the parameter, this process being described by the model

$$F_i(x) = y_i, \quad i = 1, \dots, m, \quad (2)$$

where  $F_i : D_i \subset X \rightarrow Y$ , and  $D_i$  are the corresponding domains of definition.

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Standard methods for the solution of system (2) are based in the use of *Iterative type* regularization methods [1, 8, 15, 21, 16] or *Tikhonov type* regularization methods [8, 18, 23, 20] after rewriting (2) as a single equation  $F(x) = y$ , where

$$F := (F_1, \dots, F_m) : \bigcap_{i=1}^m D_i =: D \rightarrow Y^m \quad (3)$$

and  $y := (y_1, \dots, y_m)$ . However these methods become inefficient if  $m$  is large or the evaluations of  $F_i(x)$  and  $F_i'(x)^*$  are expensive. In such a situation, Kaczmarz type methods [14, 17, 19] which cyclically consider each equation in (2) separately are much faster [19] and are often the method of choice in practice (see Subsection 1.3 below).

## 1.2 Regularization in Banach spaces

Ill-posed operator equations in Banach spaces is a fast growing area of research. Over the last seven years several theoretical results have been derived in this field, e.g,

— The classical paper on regularization of ill-posed problems in Banach spaces by Resmerita [20];

— Tikhonov regularization in Banach spaces is also investigated in [4], where two distinct iterative methods for finding the minimizer of norm-based Tikhonov functionals are proposed and analyzed (convergence is proven). Moreover, convergence rates results for Tikhonov regularization in Banach spaces are considered in [13].

— In [21] a nonlinear extension of the Landweber method to linear operator equations in Banach spaces is investigated using duality mappings. The same authors considered in [22] the solution of convex split feasibility problems in Banach spaces by cyclic projections;

— In [16] the nonlinear Landweber method and the IRGN method are considered for a single (nonlinear) operator equation in Banach spaces, and convergence results are derived. Moreover, the applicability of the proposed methods to parameter identification problems for elliptic PDEs is investigated;

— The Gauss-Newton method in Banach spaces is considered in [1] for a single operator equation in the special case  $X = Y$ . A convergence result is obtained and convergence rates (under strong source conditions) are provided.

The starting point of our approach is the Landweber method [21, 16] for solving ill-posed problems in Banach spaces.<sup>1</sup> In the case of a single operator equation, i.e.,  $m = 1$  in (2), this method is defined by

$$x_n^* = J_p(x_n) - \mu_n F'(x_n)^* J_r(F(x_n) - y^\delta), \quad x_{n+1} = J_q(x_n^*), \quad (4)$$

where  $F'(x)$  is the Fréchet derivative of  $F$  at point  $x$ , and  $J_p, J_r, J_q$  are duality mappings from  $X, Y, X^*$  to their duals respectively. Moreover,  $x_0 \in D$  and  $p, q, r \in (1, \infty)$  satisfy  $p + q = pq$ .

The step-size  $\mu_n$  depends on the constant of the tangential cone condition, the constant of the discrepancy principle, the residual at  $x_n$ , and a constant describing geometrical properties of the Banach spaces (see [21, Section 3]).

Convergence analysis for the linear case  $F \in \mathcal{L}(X, Y)$  can be found in [21], while convergence for nonlinear operator equations is derived in [16], where  $X$  is assumed to be uniformly smooth and uniformly convex (actually,  $X$  is assumed to be  $p$ -convex, which is equivalent to the dual being  $q$ -smooth, i.e., there exists a constant  $C_q > 0$  such that for all  $x^*, y^* \in X^*$  it follows  $\|x^* - y^*\|^q \leq \|x^*\|^q - q \langle J_q(x^*), y^* \rangle + C_q \|y^*\|^q$ ; see [16, Section 2.2]). For a detailed definition of smoothness, uniform smoothness and uniform convexity in Banach spaces, we refer the reader to [6, 21].

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<sup>1</sup>See also [1, 8, 15] for the analysis of the Landweber method in Hilbert spaces.

### 1.3 Landweber-Kaczmarz method in Banach spaces

The Landweber-Kaczmarz method in Banach spaces (LKB) consists in incorporating the (cyclic) Kaczmarz strategy to the Landweber method depicted in (4) for solving the system of operator equations in (2).

This strategy is analog to the one proposed in [10, 9] regarding the Landweber-Kaczmarz (LK) iteration in Hilbert spaces. See also [7] for the Steepest-Descent-Kaczmarz (SDK) iteration, [11] for the Expectation-Maximization-Kaczmarz (EMK) iteration, [3] for the Levenberg-Marquardt-Kaczmarz (LMK) iteration, and [2] for the iterated-Tikhonov-Kaczmarz (ITK) iteration.

Motivated by the ideas in the above mentioned papers (in particular by the approach in [11], where  $X = L^1(\Omega)$  and convergence is measured with respect to the Kullback-Leibler distance), we propose in this article the LBK method, which is sketched as follows:

$$x_n^* = J_p(x_n) - \mu_n F_{i_n}'(x_n)^* J_r(F_{i_n}(x_n) - y_{i_n}^\delta), \quad x_{n+1} = J_q(x_n^*), \quad (5)$$

for  $n = 0, 1, \dots$ . Moreover,  $i_n := (n \bmod m) + 1 \in \{1, \dots, m\}$ , and  $x_0 \in X \setminus \{0\}$  is an initial guess, possibly incorporating *a priori* knowledge about the exact solution (which may not be unique).

Here  $\mu_n \geq 0$  is chosen analogously as in (4) if  $\|F_{i_n}(x_n) - y_{i_n}^\delta\| \geq \tau \delta_{i_n}$  (see Section 3 for the precise definition of  $\mu_n$  and the discrepancy parameter  $\tau > 0$ ). Otherwise, we set  $\mu_n = 0$ . Consequently,  $x_{n+1} = J_q(x_n^*) = J_q(J_p(x_n)) = x_n$  every time the residual of the iterate  $x_n$  w.r.t. the  $i_n$ -th equation of system (2) drops below the discrepancy level given by  $\tau \delta_{i_n}$ .

Due to the bang-bang strategy used in to define the sequence of parameters  $(\mu_n)$ , the iteration in (5) is alternatively called loping Landweber-Kaczmarz method in Banach spaces.

As usual in Kaczmarz type algorithms, a group of  $m$  subsequent steps (beginning at some integer multiple of  $m$ ) is called a *cycle*. The iteration should be terminated when, for the first time, all of the residuals  $\|F_{i_n}(x_{n+1}) - y_{i_n}^\delta\|$  drop below a specified threshold within a cycle. That is, we stop the iteration at the step

$$\hat{n} := \min\{\ell m + (m - 1) : \ell \in \mathbb{N}, \quad \|F_i(x_{\ell m + i - 1}) - y_i^\delta\| \leq \tau \delta_i, \text{ for } 1 \leq i \leq m\}. \quad (6)$$

In other words, writing  $\hat{n} := \hat{\ell} m + (m - 1)$ , (6) can be interpreted as  $\|F_i(x_{\hat{\ell} m + i - 1}) - y_i^\delta\| \leq \tau \delta_i$ ,  $i = 1, \dots, m$ . In the case of noise free data ( $\delta_i = 0$  in (1)) the stop criteria in (6) may never be reached, i.e.,  $\hat{n} = \infty$  for  $\delta_i = 0$ .

### Outline of the manuscript

In Section 2 we introduce the notation used in this article and briefly recall some results on convex analysis and Bregman distances, which are necessary for the analysis presented in the forthcoming sections. In Section 3 the Landweber-Kaczmarz algorithm for solving systems of nonlinear ill-posed equations in Banach spaces is formulated. Moreover, some preliminary results are derived. Namely, boundedness and monotony of iteration error and residual. In Section 4 the main results of the manuscript are presented. A convergence analysis of the proposed method is given, and stability results are proven. Section 5 is devoted to conclusions and discussion of future work perspectives.

## 2 Overview on convex analysis and Bregman distances

### 2.1 Convex analysis

Let  $X$  be a (nontrivial) real Banach space with topological dual  $X^*$ . By  $\|\cdot\|$  we denote the norm on  $X$  and  $X^*$ . The duality product on  $X \times X^*$  is a bilinear symmetric mapping, denoted

by  $\langle \cdot, \cdot \rangle$ , and defined as  $\langle x, x^* \rangle = x^*(x)$ , for all  $(x, x^*) \in X \times X^*$ .

Let  $f : X \rightarrow (-\infty, \infty]$  be convex, proper and lower semicontinuous. Recall that  $f$  is convex lower semicontinuous when its epigraph  $\text{epi}(f) := \{(x, \lambda) \in X \times \mathbb{R} : f(x) \leq \lambda\}$  is a closed convex subset of  $X \times \mathbb{R}$ . Moreover,  $f$  is proper when its domain  $\text{dom}(f) := \{x \in X : f(x) < \infty\}$  is nonempty. The *subdifferential* of  $f$  is the (point-to-set) operator  $\partial f : X \rightarrow 2^{X^*}$  defined at  $x \in X$  by

$$\partial f(x) = \{x^* \in X^* : f(y) \geq f(x) + \langle x^*, y - x \rangle, \forall y \in X\}. \quad (7)$$

Notice that  $\partial f(x) = \emptyset$  whenever  $x \notin \text{dom}(f)$ . The domain of  $\partial f$  is the set  $\text{dom}(\partial f) = \{x \in X : \partial f(x) \neq \emptyset\}$ . Next we present a very useful characterization of  $\partial f$  using the concept of *Fenchel Conjugation*. The Fenchel-conjugate of  $f$  is the lower semicontinuous convex function  $f^* : X^* \rightarrow (-\infty, \infty]$  defined at  $x^* \in X^*$  by

$$f^*(x^*) = \sup_{x \in X} \langle x, x^* \rangle - f(x). \quad (8)$$

It is well known that  $f^*$  is also proper whenever  $f$  is proper. It follows directly from (8) the *Fenchel-Young* inequality

$$f(x) + f^*(x^*) \geq \langle x, x^* \rangle, \quad \forall (x, x^*) \in X \times X^*. \quad (9)$$

**Proposition 2.1.** *Let  $f : X \rightarrow (-\infty, \infty]$  be proper convex lower semicontinuous and  $(x, x^*) \in X \times X^*$ . Then  $x^* \in \partial f(x) \iff f(x) + f^*(x^*) = \langle x, x^* \rangle$ .*

*Proof.* Assume first that  $x^* \in \partial f(x)$ . Then  $\langle x, x^* \rangle \geq f(x) + (\langle y, x^* \rangle - f(y))$ ,  $\forall y \in X$ . Taking the supremum over all  $y \in X$  on the right hand side of the above inequality we obtain  $\langle x, x^* \rangle \geq f(x) + f^*(x^*)$ . Using (9) we obtain the desired identity. The proof of the reverse inequality follows the same reasoning.  $\square$

An important example considered in this article is given by  $f(x) = p^{-1}\|x\|^p$ , where  $p \in (1, \infty)$ . In this particular case, the following result can be found in [6].

**Proposition 2.2.** *Let  $p \in (1, \infty)$  and  $f : X \ni x \mapsto p^{-1}\|x\|^p \in \mathbb{R}$ . Then*

$$f^* : X^* \rightarrow \mathbb{R}, \quad x^* \mapsto q^{-1}\|x^*\|^q, \quad \text{where } p + q = pq.$$

For  $p \in (1, \infty)$ , the duality mapping  $J_p : X \rightarrow 2^{X^*}$  is defined by

$$J_p := \partial p^{-1}\|\cdot\|^p.$$

From the proposition above, we conclude that

$$x^* \in J_p(x) \iff p^{-1}\|x\|^p + q^{-1}\|x^*\|^q = \langle x, x^* \rangle, \quad p + q = pq.$$

It follows from the above identity that  $J_p(0) = \{0\}$ . On the other hand, when  $x \neq 0$ ,  $J_p(x)$  may not be singleton.

**Proposition 2.3.** *Let  $X$  and the duality mapping  $J_p$  be defined as above. The following identities hold:*

$$\begin{aligned} J_p(x) &= \{x^* \in X^* : \|x^*\| = \|x\|^{p-1} \text{ and } \langle x, x^* \rangle = \|x\| \|x^*\|\} \\ &= \{x^* \in X^* : \|x^*\| = \|x\|^{p-1} \text{ and } \langle x, x^* \rangle = \|x\|^p\} \\ &= \{x^* \in X^* : \|x^*\| = \|x\|^{p-1} \text{ and } \langle x, x^* \rangle = \|x^*\|^q\}. \end{aligned}$$

Moreover,  $J_p(x) \neq \emptyset$  for all  $x \in X$ .

*Proof.* See [21, Section 2]. □

Since  $f(x) = p^{-1}\|x\|^p$  is a continuous convex functions,  $J_p(x)$  is a singleton at  $x \in X$  iff  $f$  is Gâteaux differentiable at  $x$  [5, Corollary 4.2.5]. This motivates us to consider  $X$  a *smooth* Banach space, i.e., a Banach space having a Gâteaux differentiable norm  $\|\cdot\|_X$  on  $X \setminus \{0\}$ . As already observed,  $J_p(0) = \{0\}$  in any Banach space. In particular in a smooth Banach space  $f(x) = p^{-1}\|x\|^p$  is Gâteaux differentiable everywhere.

The next theorem describes a coercivity result related to geometrical properties of uniformly smooth Banach spaces. For details on the proof (as well as the precise definition of the constant  $G_q$ ) we refer the reader to [21, Section 2.1].

**Theorem 2.4.** *Let  $X$  be uniformly convex,  $q \in (1, \infty)$  and  $\rho_{X^*}(\cdot)$  the smoothness modulus of  $X^*$  [6]. There exists a positive constant  $G_q$  such that the function*

$$\tilde{\sigma}(x^*, y^*) := q G_q \int_0^1 (\|x^* - ty^*\| \vee \|x^*\|)^q t^{-1} \rho_{X^*} \left( t\|y^*\| / 2(\|x^* - ty^*\| \vee \|x^*\|) \right) dt$$

satisfies

$$\|x^*\|^q - q \langle J_q(x^*), y^* \rangle + \tilde{\sigma}_q(x^*, y^*) \geq \|x^* - y^*\|^q, \quad \forall x^*, y^* \in X^*.$$

## 2.2 Bregman distances

Let  $f : X \rightarrow (-\infty, \infty]$  be a proper, convex and lower semicontinuous function which is Gâteaux differentiable at  $\text{int}(\text{dom}(f))$ . Let  $f'$  denotes its Gâteaux derivative. The *Bregman distance* induced by  $f$  is defined as  $D_f : \text{dom}(f) \times \text{int}(\text{dom}(f)) \rightarrow \mathbb{R}$

$$D_f(y, x) = f(y) - (f(x) + \langle f'(x), y - x \rangle).$$

The following proposition is a useful characterization of Bregman distances using conjugate function.

**Proposition 2.5.** *Let  $f : X \rightarrow (-\infty, \infty]$  be a proper lower semicontinuous convex function which is Gâteaux differentiable at  $\text{int}(\text{dom}(f))$ . Then*

$$D_f(y, x) = f(y) + f^*(f'(x)) - \langle f'(x), y \rangle, \quad \forall (y, x) \in \text{dom}(f) \times \text{int}(\text{dom}(f)).$$

In the particular case  $f(x) = p^{-1}\|x\|^p$  ( $p \in (1, \infty)$ ) we use the notation  $D_p$  instead of  $D_f$ .

**Corollary 2.6.** *Let  $X$  be a smooth Banach space. Then  $J_p : X \rightarrow X^*$  is a single-valued mapping for which  $D_p : X \times X \rightarrow \mathbb{R}$  satisfies*

$$D_p(y, x) = p^{-1}\|y\|^p + q^{-1}\|J_p(x)\|^q - \langle y, J_p(x) \rangle = p^{-1}\|y\|^p + q^{-1}\|x\|^p - \langle y, J_p(x) \rangle.$$

**Corollary 2.7.** *Let  $X$  be a smooth Banach space. Then  $J_p : X \rightarrow X^*$  is a single-valued mapping for which  $D_p : X \times X \rightarrow \mathbb{R}$  satisfies*

$$D_p(y, x) = q^{-1}(\|x\|^p - \|y\|^p) + \langle J_p(y) - J_p(x), y \rangle.$$

### 3 A Landweber-Kaczmarz type algorithm in Banach spaces (LKB)

In this section we introduce an algorithm for solving the system of nonlinear ill-posed equations (2) with data satisfying (1). We denote by

$$\mathcal{B}_p^1(x, \rho) = \{y \in X : D_p(x, y) \leq \rho\}, \quad \mathcal{B}_p^2(x, \rho) = \{y \in X : D_p(y, x) \leq \rho\}.$$

the balls with respect to the Bregman distance  $D_p(\cdot, \cdot)$ .

A solution of (2) is any  $\bar{x} \in D$  satisfying simultaneously the operator equations in (2), while a *minimum-norm solution* of (2) in  $S$  ( $S \subset X$ ) is any solution  $x^\dagger \in S$  satisfying

$$\|x^\dagger\| = \min \{\|x\| : x \in S \text{ is a solution of (2)}\}.$$

**Assumption 3.1.** *Let  $p, q, r \in (1, \infty)$  be given with  $p + q = pq$ . The following assumptions will be required in the forthcoming analysis:*

(A0) *Each operator  $F_i$  is of class  $C^1$  in  $D$ . Moreover, the system of operator equations (2) has a solution  $\bar{x} \in X$  satisfying  $x_0 \in \mathcal{B}_p^1(\bar{x}, \bar{\rho}) \subset D$ , for some  $\bar{\rho} > 0$ , where  $x_0$  will be used as initial guess of the Landweber-Kaczmarz algorithm.*

(A1) *The family  $\{F_i\}_{1 \leq i \leq m}$  satisfies the tangential cone condition in  $\mathcal{B}_p^1(\bar{x}, \bar{\rho})$ , i.e., there exists  $\eta \in (0, 1)$  such that*

$$\|F_i(y) - F_i(x) - F'_i(x)(y - x)\| \leq \eta \|F_i(y) - F_i(x)\|,$$

for all  $x, y \in \mathcal{B}_p^1(\bar{x}, \bar{\rho})$ ,  $i = 1, \dots, m$ .

(A2) *The family  $\{F_i\}_{1 \leq i \leq m}$  satisfies the tangential cone condition in  $\mathcal{B}_p^2(x_0, \rho_0) \subset D$  for some  $\rho_0 > 0$ , i.e., there exists  $\eta \in (0, 1)$  such that*

$$\|F_i(y) - F_i(x) - F'_i(x)(y - x)\| \leq \eta \|F_i(y) - F_i(x)\|,$$

for all  $x, y \in \mathcal{B}_p^2(x_0, \rho_0)$ ,  $i = 1, \dots, m$ .

(A3) *For every  $x \in \mathcal{B}_p^1(\bar{x}, \bar{\rho})$  we have  $\|F'_i(x)\| \leq 1$ ,  $i = 1, 2, \dots, m$ .*

In the sequel we formulate our *Landweber-Kaczmarz* algorithm for approximating a solution of (2), with data given as in (1):

**ALGORITHM 3.1.** *Under assumptions (A0), (A1), choose  $c \in (0, 1)$ , and  $\tau \in (0, \infty)$  such that  $\beta := \eta + \tau^{-1}(1 + \eta) < 1$ .*

Step 0: *Set  $n = 0$  and take  $x_0 \neq 0$  satisfying (A0) and  $D_p(\bar{x}, x_0) \leq p^{-1}\|\bar{x}\|^p$ ;*

Step 1: *Set  $i_n = n(\bmod m) + 1$  and evaluate the residual  $R_n = F_{i_n}(x_n) - y_{i_n}^\delta$ ;*

Step 2: *IF ( $\|R_n\| \leq \tau\delta_{i_n}$ ) THEN*

$$\mu_n := 0;$$

*ELSE*

*Find  $\tau_n \in (0, 1]$  solving the equation*

$$\rho_{X^*}(\tau_n) \tau_n^{-1} = \left( c(1 - \beta) \|R_n\| [2^q G_q(1 \vee \|F'_{i_n}(x_n)\|) \|x_n\|]^{-1} \right) \wedge \rho_{X^*}(1); \quad (10)$$

$$\mu_n := \tau_n \|x_n\|^{p-1} / [(1 \vee \|F'_{i_n}(x_n)\|) \|R_n\|^{r-1}];$$

*ENDIF*

$$x_n^* := J_p(x_n) - \mu_n F'_{i_n}(x_n)^* J_r(F_{i_n}(x_n) - y_{i_n}^\delta);$$

$$x_{n+1} = J_q(x_n^*); \quad (11)$$

Step 3: IF  $(i_n = m)$  AND  $(x_{n+1} = x_n = \cdots = x_{n-(m-1)})$  THEN STOP;

Step 4: SET  $n = n + 1$ ; GO TO Step 1.

The next remark guarantees that the above algorithm is well defined.

**Remark 3.1.** *It is worth noticing that a solution  $\tau_n \in (0, 1]$  of equation (10) can always be found. Indeed, since  $X^*$  is uniformly smooth, the function  $(0, \infty) \ni \tau \mapsto \rho_{X^*}(\tau)/\tau \in (0, 1]$  is continuous and satisfies  $\lim_{\tau \rightarrow 0} \rho_{X^*}(\tau)/\tau = 0$  (see, e.g., [21, Definition 2.1]). For each  $n \in \mathbb{N}$ , define*

$$\lambda_n := \left( c(1 - \beta) \|R_n\| [2^q G_q(1 \vee \|F'_{i_n}(x_n)\|) \|x_n\|]^{-1} \right) \wedge \rho_{X^*}(1). \quad (12)$$

*It follows from [21, Section 2.1] that  $\rho_{X^*}(1) \leq 1$ . Therefore,  $\lambda_n \in (0, 1]$ ,  $n \in \mathbb{N}$  and we can find  $\sigma_n \in (0, 1]$  satisfying  $\rho_{X^*}(\sigma_n)/\sigma_n < \lambda_n \leq \rho_{X^*}(1)$ . Finally, the mean value theorem guarantees the existence of corresponding  $\tau_n \in (0, 1]$ , such that  $\lambda_n = \rho_{X^*}(\tau_n)/\tau_n$ ,  $n \in \mathbb{N}$ .*

Algorithm 3.1 should be stopped at the smallest iteration index  $\hat{n} \in \mathbb{N}$  of the form  $\hat{n} = \hat{\ell}m + (m - 1)$ ,  $\hat{\ell} \in \mathbb{N}$ , which satisfies

$$\|F_{i_n}(x_n) - y_{i_n}^\delta\| \leq \tau \delta_{i_n}, \quad n = \hat{\ell}m, \dots, \hat{\ell}m + (m - 1) \quad (13)$$

(notice that  $i_{\hat{n}} = m$ ). In this case,  $x_{\hat{n}} = x_{\hat{n}-1} = \cdots = x_{\hat{n}-(m-1)}$  within the  $\hat{\ell}^{\text{th}}$  cycle. The next result guarantees monotonicity of the iteration error (w.r.t. the Bregman distance  $D_p$ ) until the discrepancy principle in (13) is reached.

**Lemma 3.2** (Monotonicity). *Let assumptions (A0), (A1) be satisfied and  $(x_n)$  be a sequence generated by Algorithm 3.1. Then*

$$D_p(\bar{x}, x_{n+1}) \leq D_p(\bar{x}, x_n), \quad n = 0, 1, \dots, \hat{n},$$

where  $\hat{n} = \hat{\ell}m + (m - 1)$  is defined by (13). From the above inequality, it follows that  $x_n \in \mathcal{B}_p^1(\bar{x}, \bar{\rho}) \subset D$ ,  $n = 0, 1, \dots, \hat{n}$ .

*Proof.* Let  $0 \leq n \leq \hat{n}$  and assume that  $x_n$  is a nonzero vector satisfying  $x_n \in \mathcal{B}_p^1(\bar{x}, \bar{\rho})$ . From assumption (A0) follows  $x_n \in D$ .

If  $\|R_n\| \leq \tau \delta_{i_n}$ , then  $x_{n+1} = x_n$  and the lemma follows trivially. Otherwise, it follows from Corollary 2.6 that

$$D_p(\bar{x}, x_{n+1}) = p^{-1} \|\bar{x}\|^p + q^{-1} \|J_p(x_{n+1})\|^q - \langle \bar{x}, J_p(x_{n+1}) \rangle. \quad (14)$$

Since  $R_n = F_{i_n}(x_n) - y_{i_n}^\delta$ , we conclude from (11) and  $J_q = (J_p)^{-1}$  [6] that

$$J_p(x_{n+1}) = J_p(x_n) - \mu_n F'_{i_n}(x_n)^* J_r(R_n).$$

Thus, it follows from Theorem 2.4 that

$$\begin{aligned} \|J_p(x_{n+1})\|^q &= \|J_p(x_n) - \mu_n F'_{i_n}(x_n)^* J_r(R_n)\|^q \\ &\leq \|J_p(x_n)\|^q - q\mu_n \langle J_q(J_p(x_n)), F'_{i_n}(x_n)^* J_r(R_n) \rangle + \tilde{\sigma}_q(J_p(x_n), \mu_n F'_{i_n}(x_n)^* J_r(R_n)) \\ &= \|J_p(x_n)\|^q - q\mu_n \langle x_n, F'_{i_n}(x_n)^* J_r(R_n) \rangle + \tilde{\sigma}_q(J_p(x_n), \mu_n F'_{i_n}(x_n)^* J_r(R_n)). \end{aligned} \quad (15)$$

In order to estimate the last term on the right hand side of (15), notice that for all  $t \in [0, 1]$  the inequality

$$\begin{aligned} \|J_p(x_n) - t\mu_n F'_{i_n}(x_n)^* J_r(R_n)\| \vee \|J_p(x_n)\| &\leq \|x_n\|^{p-1} + \mu_n(1 \vee \|F'_{i_n}(x_n)\|) \|R_n\|^{r-1} \\ &\leq (1 + \tau_n) \|x_n\|^{p-1} \leq 2 \|x_n\|^{p-1} \end{aligned}$$

holds true (to obtain the first inequality we used Proposition 2.3).

Moreover,  $\|J_p(x_n) - t\mu_n F'_{i_n}(x_n)^* J_r(R_n)\| \vee \|J_p(x_n)\| \geq \|J_p(x_n)\| = \|x_n\|^{p-1}$ . These last two estimates together with the monotonicity of  $\rho_{X^*}(t)/t$ , it follows that (see Theorem 2.4)

$$\tilde{\sigma}_q(J_p(x_n), \mu_n F'_{i_n}(x_n)^* J_r(R_n)) \leq q G_q \int_0^1 \frac{(2\|x_n\|^{p-1})^q}{t} \rho_{X^*} \left( \frac{t\mu_n(1 \vee \|F'_{i_n}(x_n)\|) \|R_n\|^{r-1}}{\|x_n\|^{p-1}} \right) dt.$$

Consequently,

$$\begin{aligned} \tilde{\sigma}_q(J_p(x_n), \mu_n F'_{i_n}(x_n)^* J_r(R_n)) &\leq 2^q q G_q \|x_n\|^p \int_0^1 \rho_{X^*}(t\tau_n)/t dt \\ &= 2^q q G_q \|x_n\|^p \int_0^{\tau_n} \rho_{X^*}(t)/t dt \\ &\leq 2^q q G_q \rho_{X^*}(\tau_n)/\tau_n \|x_n\|^p \int_0^{\tau_n} dt \\ &= 2^q q G_q \rho_{X^*}(\tau_n) \|x_n\|^p. \end{aligned} \quad (16)$$

Now, substituting (16) in (15) we get the estimate

$$\|J_p(x_{n+1})\|^q \leq \|J_p(x_n)\|^q - q\mu_n \langle x_n, F'_{i_n}(x_n)^* J_r(R_n) \rangle + q 2^q G_q \rho_{X^*}(\tau_n) \|x_n\|^p.$$

From this last inequality, Corollary 2.6 and (14) we obtain

$$D_p(\bar{x}, x_{n+1}) \leq D_p(\bar{x}, x_n) - \mu_n \langle x_n - \bar{x}, F'_{i_n}(x_n)^* J_r(R_n) \rangle + 2^q G_q \rho_{X^*}(\tau_n) \|x_n\|^p. \quad (17)$$

Next we estimate the term  $\langle x_n - \bar{x}, F'_{i_n}(x_n)^* J_r(R_n) \rangle$  in (17). Since  $\bar{x}, x_n \in \mathcal{B}_p^1(\bar{x}, \rho)$ , it follows from (A1) and simple algebraic manipulations (including Proposition 2.3) that

$$\begin{aligned} \langle \bar{x} - x_n, F'_{i_n}(x_n)^* J_r(R_n) \rangle &= \langle y_{i_n} - F_{i_n}(x_n) - F'_{i_n}(x_n)(\bar{x} - x_n), -J_r(R_n) \rangle - \langle \tilde{R}_n, J_r(R_n) \rangle \\ &\leq \eta \|\tilde{R}_n\| \|J_r(R_n)\| - \langle R_n, J_r(R_n) \rangle + \langle y_{i_n} - y_{i_n}^\delta, J_r(R_n) \rangle \\ &\leq \eta (\|R_n\| + \delta_{i_n}) \|R_n\|^{r-1} - \|R_n\|^r + \delta_{i_n} \|R_n\|^{r-1} \\ &= (\eta(\|R_n\| + \delta_{i_n}) + \delta_{i_n}) \|R_n\|^{r-1} - \|R_n\|^r \\ &\leq [(\eta + \tau^{-1}(1 + \eta)) \|R_n\|] \|R_n\|^{r-1} - \|R_n\|^r \\ &= -(1 - \beta) \|R_n\|^r, \end{aligned}$$

where  $\tilde{R}_n := F_{i_n}(x_n) - y_{i_n}$  and  $\beta > 0$  is defined as in Algorithm 3.1. Substituting this last inequality in (17) yields

$$D_p(\bar{x}, x_{n+1}) \leq D_p(\bar{x}, x_n) - (1 - \beta)\mu_n \|R_n\|^r + 2^q G_q \rho_{X^*}(\tau_n) \|x_n\|^p. \quad (18)$$

Moreover, from the explicit formula for  $\mu_n$  and  $\tau_n$  (see Algorithm 3.1) we can estimate the last two terms on the right hand side of (18) by

$$\begin{aligned} -(1 - \beta)\mu_n \|R_n\|^r + 2^q G_q \rho_{X^*}(\tau_n) \|x_n\|^p &= -(1 - \beta) \frac{\tau_n \|x_n\|^{p-1} \|R_n\|}{1 \vee \|F'_{i_n}(x_n)\|} + 2^q G_q \rho_{X^*}(\tau_n) \|x_n\|^p \\ &= -(1 - \beta) \frac{\tau_n \|x_n\|^{p-1} \|R_n\|}{1 \vee \|F'_{i_n}(x_n)\|} \left( 1 - \frac{2^q G_q (1 \vee \|F'_{i_n}(x_n)\|) \|x_n\|}{(1 - \beta) \|R_n\|} \frac{\rho_{X^*}(\tau_n)}{\tau_n} \right) \\ &\leq -(1 - \beta)(1 - c) \frac{\tau_n \|x_n\|^{p-1} \|R_n\|}{1 \vee \|F'_{i_n}(x_n)\|}. \end{aligned} \quad (19)$$



Finally, substituting (19) in (18) we obtain

$$D_p(\bar{x}, x_{n+1}) \leq D_p(\bar{x}, x_n) - (1 - \beta)(1 - c)\tau_n \|x_n\|^{p-1} \|R_n\| [1 \vee \|F'_{i_n}(x_n)\|]^{-1}, \quad (20)$$

concluding the proof.  $\square$

**Remark 3.3.** *In the proof of Lemma 3.2 we used the fact that the elements  $x_n \in X$  generated by Algorithm 3.1 are a nonzero vectors. This can be verified by an inductive argument. Indeed,  $x_0 \neq 0$  is chosen in Algorithm 3.1. Assume  $x_k \neq 0$ ,  $k = 0, \dots, n$ . If  $\|R_n\| \leq \tau\delta_{i_n}$ , then  $x_{n+1} = x_n$  is also a nonzero vector. Otherwise,  $\|R_n\| > \tau\delta_{i_n} > 0$  and it follows from (20) that  $D_p(\bar{x}, x_{n+1}) < D_p(\bar{x}, x_n) \leq \dots \leq D_p(\bar{x}, x_0) \leq p^{-1}\|\bar{x}\|^p$  (the last inequality follows from the choice of  $x_0$  in Algorithm 3.1). If  $x_{n+1}$  were the null vector, we would have  $p^{-1}\|\bar{x}\|^p = D_p(\bar{x}, 0) < D_p(\bar{x}, x_n) \leq p^{-1}\|\bar{x}\|^p$  (the identity follows from Corollary 2.6), which is clearly a contradiction. Therefore,  $x_n$  is a nonzero vector, for  $n = 0, 1, \dots, \hat{n}$ .*

*In the case of exact data ( $\delta_i = 0$ ), we have  $x_n \neq 0$ ,  $n \in \mathbb{N}$ .*

The next lemma guarantees that, in the case of noisy data, Algorithm 3.1 is stopped after a finite number of cycles, i.e.,  $\hat{n} < \infty$  in (13).

**Lemma 3.4.** *Let assumptions (A0), (A1), (A3) be satisfied and  $(x_n)$  be a sequence generated by Algorithm 3.1. Then*

$$\sum_{n \in \hat{\Sigma}} \tau_n \|x_n\|^{p-1} \|R_n\| \leq (1 - \beta)^{-1} (1 - c)^{-1} D_p(\bar{x}, x_0), \quad (21)$$

where  $\hat{\Sigma} := \{n \in \{0, 1, \dots, \hat{n} - 1\} : \|R_n\| > \tau\delta_{i_n}\}$ . Additionally,

i) *In the noisy data case,  $\min\{\delta_i\}_{1 \leq i \leq m} > 0$ , Algorithm 3.1 is stopped after finitely many steps;*  
ii) *In the noise free case we have  $\lim_{n \rightarrow \infty} \|R_n\| = 0$ .*

*Proof.* Given  $n \in \hat{\Sigma}$ , it follows from (20) and (A3) that

$$(1 - \beta)(1 - c)\tau_n \|x_n\|^{p-1} \|R_n\| \leq D_p(\bar{x}, x_n) - D_p(\bar{x}, x_{n+1}). \quad (22)$$

Moreover, if  $n \notin \hat{\Sigma}$  and  $n < \hat{n}$ , we have  $0 \leq D_p(\bar{x}, x_n) - D_p(\bar{x}, x_{n+1})$ . Inequality (21) follows now from a telescopic sum argument using the above inequalities.

Add i): Assume by contradiction that Algorithm 3.1 is never stopped by the discrepancy principle. Therefore,  $\hat{n}$  defined in (13) is not finite. Consequently,  $\hat{\Sigma}$  is an infinite set (at least one step is performed in each iteration cycle).

Since  $(D_p(\bar{x}, x_n))_{n \in \hat{\Sigma}}$  is bounded, it follows that  $(\|x_n\|)_{n \in \hat{\Sigma}}$  is bounded [21, Theorem 2.12(b)]. Therefore, the sequence  $(\lambda_n)_{n \in \hat{\Sigma}}$  in (12), is bounded away from zero (see (10) and Remark 3.1), from what follows that  $(\tau_n)_{n \in \hat{\Sigma}}$  is bounded away from zero as well. From this fact

and (21) we obtain

$$\sum_{n \in \hat{\Sigma}} \|x_n\|^{p-1} < \infty.$$

Consequently,  $(x_n)_{n \in \hat{\Sigma}}$  converges to zero in  $X$  and, arguing with the continuity of  $D_p(\bar{x}, \cdot)$  [21, Theorem 2.12(c)], we conclude

$$p^{-1}\|\bar{x}\|^p = D_p(\bar{x}, 0) = \lim_{n \in \hat{\Sigma}} D_p(\bar{x}, x_n) \leq D_p(\bar{x}, x_{n'+1}) < D_p(\bar{x}, x_{n'}) \leq p^{-1}\|\bar{x}\|^p,$$

where  $n' \in \mathbb{N}$  is an arbitrary element of  $\hat{\Sigma}$  (notice that (20) holds with strict inequality for all  $n' \in \hat{\Sigma}$ ). This is clearly a contradiction. Thus,  $\hat{n}$  must be finite.

Add ii): Notice that in the noise free case we have  $\delta_i = 0$ ,  $i = 1, 2, \dots, m$ . In this particular case, (22) holds for all  $n \in \mathbb{N}$ . Consequently,

$$\sum_{n \in \mathbb{N}} \tau_n \|x_n\|^{p-1} \|R_n\| \leq (1 - \beta)^{-1} (1 - c)^{-1} D_p(\bar{x}, x_0).$$

Assume the existence of  $\varepsilon > 0$  such that the inequality  $\|R_{n_k}\| > \varepsilon$  holds true for some subsequence, and define  $\hat{\Sigma} := \{n_k; k \in \mathbb{N}\}$ . Using the same reasoning as in the proof of the second assertion we arrive at a contradiction, concluding the proof.  $\square$

## 4 Convergence analysis

In this section the main results of the manuscript are presented. A convergence analysis of the proposed method is given, and stability results are derived. We start the presentation discussing a result related to the existence of minimum-norm solutions.

**Lemma 4.1.** *Assume the continuous Fréchet differentiability of the operators  $F_i$  in  $D$ . Moreover, assume that (A2) is satisfied and also that problem (2) is solvable in  $\mathcal{B}_p^2(x_0, \rho_0)$ , where  $x_0 \in X$  and  $\rho_0 > 0$  is chosen as in (A2).*

i) *There exists a unique minimum-norm solution  $x^\dagger$  of (2) in  $\mathcal{B}_p^2(x_0, \rho_0)$ .*

ii) *If  $x^\dagger \in \text{int}(\mathcal{B}_p^2(x_0, \rho_0))$ , it can be characterized as the solution of (2) in  $\mathcal{B}_p^2(x_0, \rho_0)$  satisfying the condition*

$$J_p(x^\dagger) \in \mathcal{N}(F'_i(x^\dagger))^\perp, \quad i = 1, 2, \dots, m \quad (23)$$

(here  $A^\perp \subset X^*$  denotes the annihilator of  $A \subset X$ ).

*Proof.* As an immediate consequence of (A2) we obtain [12, Proposition 2.1]

$$F_i(z) = F_i(x) \iff z - x \in \mathcal{N}(F'_i(x)), \quad i = 1, 2, \dots, m, \quad (24)$$

for  $x, z \in \mathcal{B}_p^2(x_0, \rho_0)$ . Next we define for each  $x \in \mathcal{B}_p^2(x_0, \rho_0)$  the set  $M_x := \{z \in \mathcal{B}_p^2(x_0, \rho_0) : F_i(z) = F_i(x), i = 1, 2, \dots, m\}$ . Notice that  $M_x \neq \emptyset$ , for all  $x \in \mathcal{B}_p^2(x_0, \rho_0)$ . Moreover, it follows from (24) that

$$M_x = \bigcap_{i=1}^m \left( x + \mathcal{N}(F'_i(x)) \right) \cap \mathcal{B}_p^2(x_0, \rho_0). \quad (25)$$

Since  $D_p(\cdot, x_0)$  is continuous (see Corollary 2.6) and  $\mathcal{B}_p^2(x_0, \rho_0)$  is convex (by definition), it follows from (25) that  $M_x$  is nonempty closed and convex, for all  $x \in \mathcal{B}_p^2(x_0, \rho_0)$ . Therefore, there exists a unique  $x^\dagger \in X$  corresponding to the projection of 0 on  $M_{\bar{x}}$ , where  $\bar{x}$  is a solution of (2) in  $\mathcal{B}_p^2(x_0, \rho_0)$  [6]. This proves the first assertion.

Add ii): From the definition of  $x^\dagger$  and  $M_{\bar{x}} = M_{x^\dagger}$ , we conclude that [21, Theorem 2.5 (h)]

$$\langle J_p(x^\dagger), x^\dagger \rangle \leq \langle J_p(x^\dagger), y \rangle, \quad \forall y \in M_{x^\dagger}. \quad (26)$$

From the assumption  $x^\dagger \in \text{int}(\mathcal{B}_p^2(x_0, \rho_0))$ , it follows that given  $h \in \bigcap_{i=1}^m \mathcal{N}(F'_i(x^\dagger))$ , there exists a  $\varepsilon_0 > 0$  such that

$$x^\dagger + \varepsilon h, \quad x^\dagger - \varepsilon h \in M_{x^\dagger}, \quad \forall \varepsilon \in [0, \varepsilon_0]. \quad (27)$$

Thus, (23) follows from (26), (27) in a straightforward way. In order to prove uniqueness, let  $\tilde{x}$  be any solution of (2) in  $\mathcal{B}_p^2(x_0, \rho_0)$  satisfying

$$J_p(\tilde{x}) \in \mathcal{N}(F'_i(\tilde{x}))^\perp, \quad i = 1, 2, \dots, m. \quad (28)$$

Let  $i \in \{1, 2, \dots, m\}$ . We claim that

$$\mathcal{N}(F'_i(x^\dagger)) \subset \mathcal{N}(F'_i(\tilde{x})). \quad (29)$$

Indeed, let  $h \in \mathcal{N}(F'_i(x^\dagger))$  and set  $x_\theta = (1 - \theta)x^\dagger + \theta\tilde{x}$ , with  $\theta \in \mathbb{R}$ . Since  $x^\dagger \in \text{int}(\mathcal{B}_p^2(x_0, \rho_0))$ , we obtain a  $\theta_0 > 0$  such that  $x_\theta \in \text{int}(\mathcal{B}_p^2(x_0, \rho_0))$ , for all  $\theta \in [0, \theta_0]$ . Take  $\theta \in (0, \theta_0)$  and define  $x_{\theta, \mu} = x_\theta + \mu h$ , for  $\mu \in \mathbb{R}$ . Using the same reasoning we obtain  $\mu_0 > 0$  such that  $x_{\theta, \mu} \in \mathcal{B}_p^2(x_0, \rho_0)$ ,  $\forall \mu \in [0, \mu_0]$ .

For a fixed  $\mu \in (0, \mu_0)$ , note that  $x_{\theta, \mu} - x^\dagger = \theta(\tilde{x} - x^\dagger) + \mu h$ . Using (24) we get  $\tilde{x} - x^\dagger \in \mathcal{N}(F'_i(x^\dagger))$  and consequently  $x_{\theta, \mu} - x^\dagger \in \mathcal{N}(F'_i(x^\dagger))$ . From (24) it follows that  $F(x_{\theta, \mu}) = F(x^\dagger)$  and consequently  $F(x_{\theta, \mu}) = F(\tilde{x})$ . Applying the same reasoning as above (based on (24)) we conclude that  $x_{\theta, \mu} - \tilde{x} \in \mathcal{N}(F'_i(\tilde{x}))$ .

Since  $x_{\theta, \mu} - \tilde{x} = (1 - \theta)(x^\dagger - \tilde{x}) + \mu h$  and  $x^\dagger - \tilde{x} \in \mathcal{N}(F'_i(\tilde{x}))$  it follows  $h \in \mathcal{N}(F'_i(\tilde{x}))$ , completing the proof of our claim.

Combining (28) and (29) we obtain  $J_p(\tilde{x}) \in \mathcal{N}(F'_i(x^\dagger))^\perp$ . Consequently,  $J_p(x^\dagger) - J_p(\tilde{x}) \in \mathcal{N}(F'_i(x^\dagger))^\perp$ . Since  $x^\dagger - \tilde{x} \in \mathcal{N}(F'_i(x^\dagger))$  we conclude that  $\langle J_p(x^\dagger) - J_p(\tilde{x}), x^\dagger - \tilde{x} \rangle = 0$ . Moreover, since  $J_p$  is strictly monotone [21, Theorem 2.5(e)], we obtain  $x^\dagger = \tilde{x}$ .  $\square$

**Theorem 4.2** (Convergence for exact data). *Assume that  $\delta_i = 0$ ,  $i = 1, 2, \dots, m$ . Let the assumptions (A0), (A1), (A2) and (A3) be satisfied (for simplicity we assume  $\bar{\rho} = \rho_0$ ). Then any iteration  $(x_n)$  generated by Algorithm 3.1 converges (strongly) to a solution of (2). Additionally, if  $x^\dagger \in \text{int}(\mathcal{B}_p^2(x_0, \rho_0))$ ,  $J_p(x_0) \in \mathcal{N}(F'_i(x^\dagger))^\perp$  and  $\mathcal{N}(F'_i(x^\dagger)) \subset \mathcal{N}(F'_i(x))$ ,  $x \in B_p^1(\bar{x}, \bar{\rho})$ ,  $i = 1, 2, \dots, m$ , then  $(x_n)$  converges (strongly) to  $x^\dagger$ .*

*Proof.* From Lemma 3.2 it follows that  $D_p(\bar{x}, x_n)$  is bounded and so  $(\|x_n\|)$  is bounded. In particular,  $(J_p(x_n))$  is also bounded. Define  $\varepsilon_n = q^{-1}\|x_n\|^p - \langle \bar{x}, J_p(x_n) \rangle$ ,  $n \in \mathbb{N}$ . From Lemma 3.2 and Corollary 2.6 it follows that  $(\varepsilon_n)$  is bounded and monotone non-increasing. Thus, there exists  $\varepsilon \in \mathbb{R}$  such that  $\varepsilon_n \rightarrow \varepsilon$ , as  $n \rightarrow \infty$ .

Let  $m, n \in \mathbb{N}$  such that  $m > n$ . It follows from Corollary 2.7 that

$$D_p(x_n, x_m) = q^{-1}(\|x_m\|^p - \|x_n\|^p) + \langle J_p(x_n) - J_p(x_m), x_n \rangle = (\varepsilon_m - \varepsilon_n) + \langle J_p(x_n) - J_p(x_m), x_n - \bar{x} \rangle.$$

The first term of the above identity converges to zero, as  $m, n \rightarrow \infty$ . Notice that

$$\begin{aligned} |\langle J_p(x_n) - J_p(x_m), x_n - \bar{x} \rangle| &= \left| \left\langle \sum_{k=n}^{m-1} (J_p(x_{k+1}) - J_p(x_k)), x_n - \bar{x} \right\rangle \right| \\ &= \left| \left\langle \sum_{k=n}^{m-1} \mu_k F'_{i_k}(x_k)^* J_r(R_k), x_n - \bar{x} \right\rangle \right| \\ &\leq \sum_{k=n}^{m-1} \mu_k \|J_r(R_k)\| \|F'_{i_k}(x_k)(x_k - \bar{x})\|. \end{aligned}$$

Moreover, from (A1) we have

$$\begin{aligned} \|F'_{i_k}(x_k)(x_k - \bar{x})\| &\leq \|F_{i_k}(x_k) - F_{i_k}(\bar{x}) - F'_{i_k}(x_k)(x_k - \bar{x})\| + \|F_{i_k}(x_k) - F_{i_k}(\bar{x})\| \\ &\leq (1 + \eta) \|R_k\|. \end{aligned}$$

Therefore, using (A3) and the definition of  $\mu_k$  in Algorithm 3.1, we can estimate

$$\begin{aligned}
|\langle J_p(x_n) - J_p(x_m), x_n - \bar{x} \rangle| &\leq (1 + \eta) \sum_{k=n}^{m-1} \mu_k \|R_k\|^{r-1} \|R_k\| \\
&= (1 + \eta) \sum_{k=n}^{m-1} \frac{\tau_k \|x_k\|^{p-1} \|R_k\|^r}{(1 \vee \|F'_{i_k}(x_k)\|) \|R_k\|^{r-1}} \\
&\leq (1 + \eta) \sum_{k=n}^{m-1} \tau_k \|x_k\|^{p-1} \|R_k\|
\end{aligned}$$

(notice that the last two sums are carried out only for the terms with  $\mu_k \neq 0$ ). Consequently,  $\langle J_p(x_n) - J_p(x_m), x_n - \bar{x} \rangle$  converges to zero, from what follows  $D_p(x_n, x_m) \rightarrow 0$ , as  $m, n \rightarrow \infty$ . Therefore, we conclude that  $(x_n)$  is a Cauchy sequence, converging to some element  $\tilde{x} \in X$  [21, Theorem 2.12(b)]. Since  $x_n \in B_p^1(\bar{x}, \bar{\rho}) \subset D$ , for  $n \in \mathbb{N}$ , it follows that  $\tilde{x} \in D$ . Moreover, from the continuity of  $D_p(\cdot, \tilde{x})$ , we have  $D_p(x_n, \tilde{x}) \rightarrow D_p(\tilde{x}, \tilde{x}) = 0$ , proving that  $\|x_n - \tilde{x}\| \rightarrow 0$ .

Let  $i \in \{1, 2, \dots, m\}$  and  $\varepsilon > 0$ . Since  $F_i$  is continuous, we have  $F_i(x_n) \rightarrow F_i(\tilde{x})$ ,  $n \rightarrow \infty$ . This fact together with  $R_n \rightarrow 0$ , allow us to find an  $n_0 \in \mathbb{N}$  such that

$$\|F_i(x_n) - F_i(\tilde{x})\| < \varepsilon/2, \quad \|F_{i_n}(x_n) - y_{i_n}\| < \varepsilon/2, \quad \forall n \geq n_0.$$

Let  $\tilde{n} \geq n_0$  be such that  $i_{\tilde{n}} = i$ . Then  $\|F_i(\tilde{x}) - y_i\| \leq \|F_i(x_{\tilde{n}}) - F_i(\tilde{x})\| + \|F_{i_{\tilde{n}}}(x_{\tilde{n}}) - y_{i_{\tilde{n}}}\| < \varepsilon$ . Thus,  $F_i(\tilde{x}) = y_i$ , proving that  $\tilde{x}$  is a solution of (2).

For each  $n \in \mathbb{N}$  it follows from (11) and the theorem assumption that

$$J_p(x_n) - J_p(x_0) \in \bigcap_{k=0}^{n-1} \mathcal{N}(F'_{i_k}(x_k))^\perp \subset \bigcap_{k=0}^{n-1} \mathcal{N}(F'_{i_k}(x^\dagger))^\perp.$$

Moreover, due to  $J_p(x_0) \in \mathcal{N}(F'_i(x^\dagger))^\perp$ ,  $i = 1, 2, \dots, m$ , we have  $J_p(x_n) \in \bigcap_{j=1}^m \mathcal{N}(F'_j(x^\dagger))^\perp$ ,  $n \geq m$ . Then  $J_p(x_n) \in \mathcal{N}(F'_i(x^\dagger))^\perp$ , for  $n \geq m$ . Since  $J_p$  is continuous and  $x_n \rightarrow \tilde{x}$ , we conclude that  $J_p(\tilde{x}) \in \mathcal{N}(F'_i(x^\dagger))^\perp$ . However, due to  $\mathcal{N}(F'_i(\tilde{x})) = \mathcal{N}(F'_i(x^\dagger))$  (which follows from  $F_i(\tilde{x}) = F_i(x^\dagger)$ ) we conclude that  $J_p(\tilde{x}) \in \mathcal{N}(F'_i(\tilde{x}))^\perp$ , proving that  $\tilde{x} = x^\dagger$ .  $\square$

In the sequel we prove a convergence result in the noisy data case. For simplicity of the presentation, we assume for the rest of this section that  $\delta_1 = \delta_2 = \dots = \delta_m = \delta > 0$ . Moreover, we denote by  $(x_n)$ ,  $(x_n^\delta)$  the iterations generated by Algorithm 3.1 with exact data and noisy data respectively.

**Theorem 4.3** (Semi-convergence). *Let  $Y$  be an uniformly smooth Banach space and assumptions (A0), (A1), (A2) and (A3) be satisfied (for simplicity we assume  $\bar{\rho} = \rho_0$ ). Moreover, let  $(\delta_k > 0)_{k \in \mathbb{N}}$  be a sequence satisfying  $\delta_k \rightarrow 0$  and  $y_i^k \in Y$  be corresponding noisy data satisfying  $\|y_i^k - y_i\| \leq \delta_k$ ,  $i = 1, \dots, m$ , and  $k \in \mathbb{N}$ .*

*If (for each  $k \in \mathbb{N}$ ) the iterations  $(x_n^{\delta_k})$  are stopped according to the discrepancy principle (13) at  $\hat{n}_k = \hat{n}(\delta_k)$ , then  $(x_{\hat{n}_k}^{\delta_k})$  converges (strongly) to a solution  $\tilde{x} \in B_p^1(\bar{x}, \bar{\rho})$  of (2) as  $k \rightarrow \infty$ .*

*Additionally, if  $x^\dagger \in \text{int}(\mathcal{B}_p^2(x_0, \rho_0))$ ,  $J_p(x_0) \in \mathcal{N}(F'_i(x^\dagger))^\perp$  and  $\mathcal{N}(F'_i(x^\dagger)) \subset \mathcal{N}(F'_i(x))$ ,  $x \in B_p^1(\bar{x}, \bar{\rho})$ ,  $i = 1, 2, \dots, m$ , then  $(x_{\hat{n}_k}^{\delta_k})$  converges (strongly) to  $x^\dagger$  as  $k \rightarrow \infty$ .*

*Proof.* For each  $k \in \mathbb{N}$  we can write  $\hat{n}_k$  in (13) in the form  $\hat{\ell}_k m + (m - 1)$ . Thus,  $x_{\hat{n}_k}^{\delta_k} = x_{\hat{n}_k - 1}^{\delta_k} = \dots = x_{\hat{n}_k - (m-1)}^{\delta_k}$  and

$$\|F_{i_n}(x_{\hat{n}_k}^{\delta_k}) - y_{i_n}^k\| \leq \tau \delta_k, \quad n = \hat{\ell}_k m, \dots, \hat{\ell}_k m + (m - 1).$$

Since  $i_n = 1, 2, \dots, m$  as  $n = \hat{\ell}_k m, \dots, \hat{\ell}_k m + (m - 1)$ , it follows that

$$\|F_i(x_{\hat{n}_k}^{\delta_k}) - y_i^k\| \leq \tau \delta_k, \quad i = 1, 2, \dots, m. \quad (30)$$

At this point we must consider two cases separately:

**Case 1:** The sequence  $(\hat{n}_k) \in \mathbb{N}$  is bounded.

If this is the case, we can assume the existence of  $\hat{n} \in \mathbb{N}$  such that  $\hat{n}_k = \hat{n}$ , for all  $k \in \mathbb{N}$ . Notice that, for each  $k \in \mathbb{N}$ , the sequence element  $x_{\hat{n}_k}^{\delta_k}$  depends continuously on the corresponding data  $(y_i^k)_{i=1}^m$  (this is the point where the uniform smoothness of  $Y$  is required). Therefore, it follows that

$$x_{\hat{n}_k}^{\delta_k} \rightarrow x_{\hat{n}}, \quad F_i(x_{\hat{n}_k}^{\delta_k}) \rightarrow F_i(x_{\hat{n}}), \quad k \rightarrow \infty, \quad (31)$$

for each  $i = 1, 2, \dots, m$ . Since each operator  $F_i$  is continuous, taking limit as  $k \rightarrow \infty$  in (30) gives  $F_i(x_{\hat{n}}) = y_i$ ,  $i = 1, 2, \dots, m$ , which proves that  $\tilde{x} := x_{\hat{n}}$  is a solution of (2).

**Case 2:** The sequence  $(\hat{n}_k) \in \mathbb{N}$  is unbounded.

We can assume that  $\hat{n}_k \rightarrow \infty$ , monotonically. Due to Theorem 4.2,  $(x_{\hat{n}_k})$  converges to some solution  $\tilde{x} \in B_p^1(\tilde{x}, \bar{\rho})$  of (2). Therefore,  $D_p(\tilde{x}, x_{\hat{n}_k}) \rightarrow 0$ . Thus, given  $\varepsilon > 0$ , there exists  $N \in \mathbb{N}$  such that

$$D_p(\tilde{x}, x_{\hat{n}_k}) < \varepsilon/2, \quad \forall \hat{n}_k \geq N.$$

Since  $x_{\hat{n}_k}^{\delta_k} \rightarrow x_N$  as  $k \rightarrow \infty$ , and  $D_p(\tilde{x}, \cdot)$  is continuous, there exists  $\tilde{k} \in \mathbb{N}$  such that

$$|D_p(\tilde{x}, x_{\hat{n}_k}^{\delta_k}) - D_p(\tilde{x}, x_N)| < \varepsilon/2, \quad \forall k \geq \tilde{k}.$$

Consequently,

$$D_p(\tilde{x}, x_{\hat{n}_k}^{\delta_k}) = D_p(\tilde{x}, x_N) + D_p(\tilde{x}, x_{\hat{n}_k}^{\delta_k}) - D_p(\tilde{x}, x_N) < \varepsilon, \quad \forall k \geq \tilde{k}.$$

Since  $D_p(\tilde{x}, x_{\hat{n}_k}^{\delta_k}) \leq D_p(\tilde{x}, x_N)$ , for all  $\hat{n}_k > N$ , it follows that  $D_p(\tilde{x}, x_{\hat{n}_k}^{\delta_k}) < \varepsilon$  for  $k$  large enough. Therefore, due to [21, Theorem 2.12(d)], we conclude that  $(x_{\hat{n}_k}^{\delta_k})$  converges to  $\tilde{x}$ .

To prove the last assertion, it is enough to observe that, due to the extra assumption,  $\tilde{x} = x^\dagger$  must hold.  $\square$

## 5 Conclusions and future work

In this manuscript we proposed a Landweber-Kaczmarz type iteration for regularizing systems of nonlinear ill-posed operator equations in Banach spaces. We extended the results in [21], which considered the case of a single linear operator equation and obtained convergence and stability results for the Landweber iteration. Our results also extend the one obtained in [16], where nonlinear operator equations are considered in Banach spaces, but under the stronger assumption that  $X$  is  $p$ -convex.

One future perspective is to perform numerical experiments for the LKB method applied to parameter identification problems related to elliptic equations as the ones described in the last section of [16]. Another possible research direction is to extend the convergence analysis in this article (in the framework of Banach spaces) to the Steepest-Descent-Kaczmarz (SDK) iteration [7], the Levenberg-Marquardt-Kaczmarz (LMK) iteration [3], and the iterated-Tikhonov-Kaczmarz (iTK) iteration [2]

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