

# A NEW SPLIT INVERSE PROBLEM AND AN APPLICATION TO LEAST INTENSITY FEASIBLE SOLUTIONS

# AVIV GIBALI

ABSTRACT. In this paper we propose a new prototypical split inverse problem (SIP) which we call the general split common fixed points problem. We introduce iterative projection methods for solving this problem in real Hilbert space. Two strong convergence theorems are presented in the spirit of Măruşter and Popirlan and of Baillon, Bruck and Reich.

As application we show how the new SIP modeling can be used to solve the best approximation problem of the split convex feasibility problem and obtain a minimum norm solution or least intensity feasible solution in the field of intensitymodulated radiation therapy. We compare the performance of our scheme on Dang and Xue example.

#### 1. INTRODUCTION

The main purpose of this manuscript is to present a new instance of the *Split Inverse Problem* (SIP) (formulated in [19, Section 2]). In order to present the new problem formulation a survey of SIPs is given. Afterwards we present iterative projection methods for solving the problem and prove two strong convergence theorems of the generated sequences in real Hilbert space.

The SIP concerns a model in which there are given two vector spaces X and Y and a bounded linear operator  $A : X \to Y$ . In addition, two inverse problems are involved. The first one, denoted by IP<sub>1</sub>, is formulated in the space X and the second one, denoted by IP<sub>2</sub>, is formulated in the space Y. Given these data, the Split Inverse Problem (SIP) is formulated as follows:

(1.1) find a point  $x^* \in X$  that solves IP<sub>1</sub>

and such that

(1.2) the point 
$$y^* = Ax^* \in Y$$
 solves IP<sub>2</sub>.

In order to illustrate the generality of this split inverse problem modeling we wish to present several special cases which are studied intensively in the literature. We first start with the formulation of the *Convex Feasibility Problem* (CFP) which stands at the core of the modeling of many inverse problems in various areas of mathematics

<sup>2010</sup> Mathematics Subject Classification. 49M37, 65K15, 90C25.

Key words and phrases. Split inverse problem, iterative methods, product space, intensity-modulated radiation therapy, minimum-norm solution.

This work is supported by the EU FP7 IRSES program STREVCOMS, grant no. PIRSES-GA-2013-612669.

and the physical sciences; for example in sensor networks, in radiation therapy treatment planning, in color imaging and in adaptive filtering, see e.g., [14, 7, 9, 16] and references therein.

## Problem 1.1. The Convex Feasibility Problem (CFP).

Let  $\mathcal{H}$  be real Hilbert space and for i = 1, ..., p let  $C_i \subseteq \mathcal{H}$  be closed and convex sets. The CFP is:

(1.3) find a point 
$$x^* \in \mathbf{C} := \bigcap_{i=1}^p C_i$$
.

The first instance of the split inverse problems is due to Censor and Elfving in [17] and called the *Split Convex Feasibility Problem* (SCFP) which is a SIP with IP<sub>1</sub> and IP<sub>2</sub> as CFPs. This reformulation was employed for solving an inverse problem in intensity-modulated radiation therapy (IMRT) treatment planning, see [15]. Other real-world application for the SCFP include the Multi-Domain Adaptive Filtering (MDAF) [41] and navigation on the Pareto frontier in Multi-Criteria Optimization, see [24].

The problem formulates as follows.

# Problem 1.2. The Split Convex Feasibility Problem (SCFP).

Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces. Let  $C \subseteq \mathcal{H}_1$  and  $Q \subseteq \mathcal{H}_2$  be two non-empty, closed and convex sets, in addition given a bounded linear operator  $A: \mathcal{H}_1 \to \mathcal{H}_2$ , the SCFP is:

(1.4) find a point 
$$x^* \in C$$
 such that  $y^* = Ax^* \in Q$ .

The next natural development is a SCFP which allows a finite number of nonempty, closed and convex sets in the spaces  $\mathcal{H}_1$  and  $\mathcal{H}_2$ , respectively, [18].

# Problem 1.3. The Multiple Set Split Convex Feasibility Problem (MSS-CFP).

Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces and let r and p be two natural numbers. Given  $C_i$ ,  $1 \leq i \leq p$  and  $Q_j$ ,  $1 \leq j \leq r$ , closed and convex subsets of  $\mathcal{H}_1$  and  $\mathcal{H}_2$  respectively and a bounded linear operator  $A : \mathcal{H}_1 \to \mathcal{H}_2$ . The MSSCFP is to find a point  $x^*$  such that

(1.5) 
$$x^* \in \boldsymbol{C} := \bigcap_{i=1}^p C_i \text{ such that } Ax^* \in \boldsymbol{Q} := \bigcap_{j=1}^r Q_j.$$

Masad and Reich [29] generalized the MSSCFP in which several bounded and linear operators  $A_j : \mathcal{H}_1 \to \mathcal{H}_2$  are involved.

# Problem 1.4. The Constrained Multiple Set Split Convex Feasibility Problem (CMSSCFP).

Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces and let r and p be two natural numbers. Given  $C_i$ ,  $1 \leq i \leq p$  and  $Q_j$ ,  $1 \leq j \leq r$ , closed and convex subsets of  $\mathcal{H}_1$  and  $\mathcal{H}_2$  respectively; further, for  $1 \leq j \leq r$  let  $A_j : \mathcal{H}_1 \to \mathcal{H}_2$  be bounded linear operators. In addition let  $\Omega$  be another convex subsets of  $\mathcal{H}_1$ . The CMSSCFP is to find a point  $x^* \in \Omega$  such that

(1.6) 
$$x^* \in \bigcap_{i=1}^p C_i \text{ such that } A_j x^* \in Q_j.$$

Censor and Segal [21] replaced the CFPs in the above split inverse problem with fixed points problems.

### Problem 1.5. The Split Common Fixed Points Problem (SCFPP).

Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces and let r and p be two natural numbers. Given operators  $U_i : \mathcal{H}_1 \to \mathcal{H}_1, 1 \leq i \leq p$ , and  $T_j : \mathcal{H}_2 \to \mathcal{H}_2, 1 \leq j \leq r$ , with non-empty fixed points sets Fix  $(U_i) = C_i, 1 \leq i \leq p$  and Fix  $(T_j) = Q_j, 1 \leq j \leq r$ , respectively and bounded linear operator  $A : \mathcal{H}_1 \to \mathcal{H}_2$ . The SCFPP is to find a point  $x^*$  such that

(1.7) 
$$x^* \in \bigcap_{i=1}^p C_i \text{ such that } Ax^* \in \mathbf{Q} = \bigcap_{j=1}^r Q_j.$$

Censor, Gibali and Reich [19] introduced the following *Split Variational Inequality Problem* (SVIP).

## Problem 1.6. The Split Variational Inequality Problem (SVIP).

Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces. Given operators  $f : \mathcal{H}_1 \to \mathcal{H}_1$  and  $g : \mathcal{H}_2 \to \mathcal{H}_2$ , a bounded linear operator  $A : \mathcal{H}_1 \to \mathcal{H}_2$ , and non-empty, closed and convex sets  $C \subseteq \mathcal{H}_1$  and  $Q \subseteq \mathcal{H}_2$ . The SVIP is formulated as follows:

(1.8) find a point 
$$x^* \in C$$
 such that  $\langle f(x^*), x - x^* \rangle \ge 0$  for all  $x \in C$   
and such that

(1.9) the point 
$$y^* = Ax^* \in Q$$
 solves  $\langle g(y^*), y - y^* \rangle \ge 0$  for all  $y \in Q$ .

Moudafi [31] generalized the SVIP and introduced the *Split Monotone Variational Inclusion* (SMVI).

**Problem 1.7. The** Split Monotone Variational Inclusion (SMVI). Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces. Given two operators  $f : \mathcal{H}_1 \to \mathcal{H}_1$  and  $g : \mathcal{H}_2 \to \mathcal{H}_2$ , a bounded linear operator  $A : \mathcal{H}_1 \to \mathcal{H}_2$ , and two set-valued mappings  $B_1 : \mathcal{H}_1 \to 2^{\mathcal{H}_1}$  and  $B_2 : \mathcal{H}_2 \to 2^{\mathcal{H}_2}$ , the SMVI is formulated as follows:

(1.10) find a point 
$$x^* \in \mathcal{H}_1$$
 such that  $0 \in f(x^*) + B_1(x^*)$ 

and such that the point

(1.11) 
$$y^* = Ax^* \in \mathcal{H}_2 \text{ solves } 0 \in g(y^*) + B_2(y^*).$$

Byrne, Censor, Gibali and Reich [10] generalized and introduced the following *Split Common Null Point Problem* (SCNPP).

# Problem 1.8. The Split Common Null Point Problem (SCNPP).

Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces. Given set-valued mappings  $B_i : \mathcal{H}_1 \to 2^{\mathcal{H}_1}$ ,  $1 \leq i \leq p$ , and  $F_j : \mathcal{H}_2 \to 2^{\mathcal{H}_2}$ ,  $1 \leq j \leq r$ , respectively, and bounded linear operators  $A_j : \mathcal{H}_1 \to \mathcal{H}_2$ ,  $1 \leq j \leq r$ , the SCNPP is formulated as follows:

(1.12) find a point 
$$x^* \in \mathcal{H}_1$$
 such that  $0 \in \bigcap_{i=1}^p B_i(x^*)$ 

and such that the points

(1.13) 
$$y_j^* = A_j x^* \in \mathcal{H}_2 \text{ solve } 0 \in \bigcap_{i=1}^r F_j(y_j^*).$$

Following the above SIPs we wish to introduce a new SIP which is a generalization of the split common fixed points problem.

**Problem 1.9. The General Split Common Fixed Points Problem (GSCFPP).** Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces and let r and p be two natural numbers. Given operators  $U_i : \mathcal{H}_1 \to \mathcal{H}_1, 1 \leq i \leq p$ , and  $T_j : \mathcal{H}_2 \to \mathcal{H}_2, 1 \leq j \leq r$ , with

non-empty fixed points sets  $\operatorname{Fix}(U_i) = C_i$ ,  $1 \leq i \leq p$  and  $\operatorname{Fix}(T_j) = Q_j$ ,  $1 \leq j \leq r$ , respectively; further, for  $1 \leq j \leq r$  let  $A_j : \mathcal{H}_1 \to \mathcal{H}_2$  be bounded linear operators. The problem is

(1.14) find a point  $x^* \in \mathbf{C} := \bigcap_{i=1}^p C_i$  such that  $A_j x^* \in Q_j$ .

Our main contribution in this manuscript is not only the introductory of the new SIP instance but also the kind of operators involved, which are demicontractive, and the strong convergence theorems of the proposed algorithms. The analysis combines arguments from Moudafi [30] and Senter and Dotson [37]. We also present a special case of the problem with firmly nonexpansive operators.

The paper is organized as follows. In Section 2, we collect some definitions of operator classes that will be needed later on. In Section 3, we present and analyze our main result which consists of strong convergence theorems for demicontractive operators as well as for the special case of firmly nonexpansive operators. Finally in Section 4 we illustrate the performance of our proposed scheme to find a minimum solution of a SCFP which is motivated from the field of intensity-modulated radiation therapy (IMRT) treatment planning and called there least-intensity feasible solution.

# 2. Preliminaries

Let  $\mathcal{H}$  be a real Hilbert space with inner product  $\langle \cdot, \cdot \rangle$  and norm  $\|\cdot\|$ , and let D be a non-empty, closed and convex subset of  $\mathcal{H}$ . We write  $x^k \to x$  and  $x^k \to x$  to indicate that the sequence  $\{x^k\}_{k=0}^{\infty}$  converges weakly and strongly to x, respectively. Next we present some properties of operators, which will be useful later on.

**Definition 2.1.** Let  $h : \mathcal{H} \to \mathcal{H}$  be an operator and  $D \subseteq \mathcal{H}$ .

• The operator h is called  $\nu$ -inverse strongly monotone ( $\nu$ -ism) on D if there exists  $\nu \ge 0$  such that

(2.1) 
$$\langle h(x) - h(y), x - y \rangle \ge \nu \|h(x) - h(y)\|^2 \text{ for all } x, y \in D.$$

• The operator h is called firmly nonexpansive, if

(2.2) 
$$\langle h(x) - h(y), x - y \rangle \ge \|h(x) - h(y)\|^2$$
 for all  $x, y \in D$ ,  
i. e., 1-ism.

• The operator h is called Lipschitz continuous with constant  $\kappa > 0$  on D, if

(2.3) 
$$||h(x) - h(y)|| \le \kappa ||x - y|| \text{ for all } x, y \in D.$$

• The operator h is called nonexpansive, if

(2.4) 
$$||h(x) - h(y)|| \le ||x - y||$$
 for all  $x, y \in D$ .

• The operator h is called quasi-nonexpansive, if

(2.5) 
$$||h(x) - q|| \le ||x - q||$$
 for all  $(x, q) \in D \times Fix(h)$ 

here Fix(h) denotes the fixed points set of h, that is

(2.6) 
$$\operatorname{Fix}(h) := \{x \in \mathcal{H} \mid h(x) = x\}.$$

• The operator h is called firmly quasi-nonexpansive [39, 40, Section B] and [27], namely

(2.7) 
$$||h(x) - q||^2 \le ||x - q||^2 - ||x - h(x)||^2$$
 for all  $(x, q) \in D \times \text{Fix}(h)$ .

In the literature one can find different names for firmly quasi nonexpansive operators. The term cutter was introduced by Cegielski and Censor in [13], Bauschke and Combettes call it the  $\mathcal{T}$ -class [2]. Zaknoon [42], and Segal and Censor [36, 21] called it directed operator and in [11] these operators were called separating operators. Another equavalent definition for this class of operators is, dom  $h = \mathcal{H}$  and

(2.8) 
$$\langle h(x) - x, h(x) - q \rangle \le 0 \text{ for all } (x,q) \in D \times \operatorname{Fix}(h).$$

• The operator h is called **averaged** if there exists a nonexpansive operator  $N: \mathcal{H} \to \mathcal{H}$  and a number  $c \in (0, 1)$  such that

(2.9) 
$$h = (1 - c)I + cN,$$

we say that h is c-av.

(i) It can be easily verified that if h is  $\nu$ -ism, then it is Lipschitz continuous with constant  $1/\nu$ . (ii) It is known that an operator h is averaged if and only if its complement G := I - h is  $\nu$ -ism for some  $\nu > 1/2$ , see, e.g., [9, Lemma 2.1]. (iii) A well known identity relates an operator h to its complement G

(2.10) 
$$||x - y||^2 - ||h(x) - h(y)||^2 = 2 \langle G(x) - G(y), x - y \rangle - ||G(x) - G(y)||^2.$$

It follows immediately that the operator h is nonexpansive if and only if G is 1/2-ism.

- The operator h is called a strongly nonexpansive [6] if it is nonexpansive and whenever  $\{x^k y^k\}_{k=1}^{\infty}$  is bounded and  $||x^k y^k|| ||h(x^k) h(y^k)|| \to 0$ , it follows that  $(x^k y^k) (h(x^k) h(y^k)) \to 0$ .
- The operator h is called demicontractive operator [28] (see also [5, 25, 32]), if the exists  $\beta \in [0, 1)$  such that

(2.11) 
$$||h(x) - q||^2 \le ||x - q||^2 + \beta ||x - h(x)||^2$$
 for all  $(x, q) \in D \times \text{Fix}(h)$ ,

which is equivalent to

(2.12) 
$$\langle x - h(x), x - q \rangle \ge \frac{1 - \beta}{2} ||x - h(x)||^2 \text{ for all } (x, q) \in D \times \operatorname{Fix}(h).$$

- The operator h is called demiclosed [4, Definition 2] at y ∈ H, if for any sequence {x<sup>k</sup>}<sub>k=0</sub><sup>∞</sup> such that x<sup>k</sup> → x̄ and h(x<sup>k</sup>) → y, we have h(x̄) = y.
  The operator for a substantial constant is called a constant in a substant [6] if
- The operator h is called a asymptotically regular [6] if

(2.13) 
$$\lim_{k \to \infty} (h^k(x) - h^{k+1}(y)) = 0 \text{ for all } x \in \mathcal{H}.$$

where  $h^k$  denotes the k iterate of h.

• The operator h is called odd if

(2.14) 
$$h(-x) = -h(x) \text{ for all } x \in \mathcal{H}.$$

The Demiclosedness Principle. Let  $\mathcal{H}$  be a real Hilbert space, D a closed and convex subset of  $\mathcal{H}$ , and  $N: D \to \mathcal{H}$  a nonexpansive operator. Then I - N (Iis the identity operator of  $\mathcal{H}$ ) is demiclosed at  $y \in \mathcal{H}$ .

If I - h (*I* is the identity operator) is demiclosed at 0 we get  $x^k \rightarrow \overline{x}$  and  $(I - h)x^k \rightarrow y$ , implies  $\overline{x} \in \text{Fix}(h)$ .

**Definition 2.2.** Let  $\mathcal{H}$  be a real Hilbert space and  $\{x^k\}_{k=0}^{\infty} \subset \mathcal{H}$ . Given a closed subset  $M \subseteq \mathcal{H}$ , we say that  $\{x^k\}_{k=0}^{\infty}$  is regular with respect to M if

(2.15) 
$$\lim_{k \to \infty} \operatorname{dist}(x^k, M) = 0.$$

Next we recall Opial's Theorem [33], also known in the literature as the Krasnosel'skiĭ-Mann Theorem.

**Theorem 2.3.** Let  $\mathcal{H}$  be a real Hilbert space and  $D \subset \mathcal{H}$  be closed and convex. Assume that  $h: D \to D$  is an averaged operator with  $\operatorname{Fix}(h) \neq \emptyset$ . Then, for an arbitrary  $x^0 \in D$ , the sequence

(2.16) 
$$x^{k+1} = h(x^k)$$

converges weakly to  $x^* \in Fix(h)$ .

The convergence obtained in Theorem 2.3 is not strong in general [23, 3]!

### 3. Main result

In order to present our algorithm for solving Problem 1.9 and its strong convergence theorem we first discuss the case of two operators split common fixed point problem, and then by using an appropriate product space reformulation we show how the general case can be presented as a two operators split common fixed point problem.

3.1. The two operators split common fixed points problem. Now we are focus in Problem 1.9 where p, r = 1. In this case there is one linear bounded operator  $A : \mathcal{H}_1 \to \mathcal{H}_2$  and  $U : \mathcal{H}_1 \to \mathcal{H}_1$ ,  $T : \mathcal{H}_2 \to \mathcal{H}_2$  demicontractive operators (with constants  $\beta$  and  $\mu$ , respectively). We assume the non-emptness of Fix (U) = Cand Fix (T) = Q. The two operators split common fixed points problem is to find a point  $x^*$  such that

$$(3.1) x^* \in C \text{ and } Ax^* \in Q.$$

Let us denote the solution set of the two operators SCFPP by

(3.2) 
$$\Gamma \equiv \Gamma(U,T) := \{ y \in C \mid Ay \in Q \}.$$

If (3.1) is restricted to Euclidean spaces and both U and T are cutters, then Censor and Segal [21] presented the following algorithm.

# Algorithm 3.1.

**Initialization:** Let  $x^0 \in \mathcal{H}_1$  be arbitrary. **Iterative step:** For  $k \ge 0$  let

(3.3) 
$$x^{k+1} = U\left(x^k + \gamma A^*(T-I)(Ax^k)\right),$$

where  $\gamma \in (0, 2/L)$ , L is the spectral radius of the operator  $A^*A$  ( $A^*$  is the adjoint of A).

In case where U and T are demicontractive, Moudafi presented the following algorithm.

### Algorithm 3.2.

**Initialization:** Let  $x^0 \in \mathcal{H}_1$  be arbitrary. **Iterative step:** For  $k \ge 0$  set  $u^k = x^k + \gamma A^*(T-I)Ax^k$  and let

(3.4) 
$$x^{k+1} = (1 - \alpha_k)u^k + \alpha_k U\left(u^k\right),$$

where  $\gamma \in (0, (1 - \mu)/L)$ , L is the spectral radius of the operator  $A^*A$ ,  $\mu$  is the demicontractivity constant of U and  $\{\alpha_k\}_{k=0}^{\infty} \subset (0, 1)$ .

Moudafi's weak convergence theorem [30, Theorem 2.1] of Algorithm 3.2 is next.

**Theorem 3.3.** Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces and let  $A : \mathcal{H}_1 \to \mathcal{H}_2$  be a linear bounded operator. Let  $U : \mathcal{H}_1 \to \mathcal{H}_1$  and  $T : \mathcal{H}_2 \to \mathcal{H}_2$  be demicontractive operators (with constants  $\beta$  and  $\mu$ ) with non-empty Fix (U) = C and Fix (T) = Q. Assume that U - I and T - I are demiclosed at 0. If  $\Gamma \neq \emptyset$  then any sequence  $\{x^k\}_{k=0}^{\infty}$ , generated by Algorithm 3.2 converges weakly to  $x^* \in \Gamma$ , provided that  $\gamma \in (0, (1 - \mu)/L)$  and  $\{\alpha_k\}_{k=0}^{\infty} \subset (\delta, 1 - \beta - \delta)$  for small enough  $\delta > 0$ .

Since our goal is to obtain strong convergence theorem of Algorithm 3.2, we can discuss the following Senter and Dotson [37] condition.

**Condition 3.4.** There exists a nondecreasing function  $f : [0, \infty) \to [0, \infty)$  with f(0) = 0 and f(r) > 0 for all r > 0, such that

(3.5) 
$$f(\operatorname{dist}(x,\operatorname{Fix}(T)) \le ||x - T(x)||.$$

Petryshyn and Williamson [34], point out the significant role of the behavior of a sequence  $\{x^k\}_{k=0}^{\infty}$  with respect to the set of fixed points in the following theorem.

**Theorem 3.5.** Petryshyn and Williamson [34]. Let  $\mathcal{H}$  be a real Hilbert space,  $T: D \subset \mathcal{H} \to \mathcal{H}$  a quasi-nonexpansive operator such that  $\operatorname{Fix}(T)$  is non-empty and closed set. Let  $x^0 \in D$  such that  $x^k = T^k(x^0)$ . Then the sequence  $\{x^k\}_{k=0}^{\infty}$ converges strongly to a fixed point of T if and only if  $\{x^k\}_{k=0}^{\infty}$  is regular with respect to  $\operatorname{Fix}(T)$ .

Following this theorem, Măruşter and Popirlan [28] proved that any sequence  $\{x^k\}_{k=0}^{\infty}$  generated by the Mann iteration with demicontractive operator converges strongly to Fix(T) if and only if it is regular with respect to Fix(T).

Inspired by the above works we are able to present strong convergence theorem for Algorithm 3.2 using either Condition 3.4 or regularity assumption. The proof uses a similar arguments as in [26, Theorem 2].

**Theorem 3.6.** Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces and let  $A : \mathcal{H}_1 \to \mathcal{H}_2$  be a linear bounded operator. Let  $U : \mathcal{H}_1 \to \mathcal{H}_1$  and  $T : \mathcal{H}_2 \to \mathcal{H}_2$  be a demicontractive operators (with constants  $\beta$  and  $\mu$ , respectively) with non-empty Fix (U) = C and

Fix (T) = Q. Assume that U - I and T - I are demiclosed at 0 and there exists  $0 \neq \sigma \in \mathcal{H}_1$  such that

(3.6) 
$$\begin{cases} \langle U(y) - y, \sigma \rangle \leq 0 \text{ for all } y \in \mathcal{H}_1, \\ \langle A^*(T - I)Ay, \sigma \rangle \leq 0 \text{ for all } y \in \mathcal{H}_1. \end{cases}$$

If  $\Gamma \neq \emptyset$  then for a suitable  $x^0 \in \mathcal{H}_1$  any sequence  $\{x^k\}_{k=0}^{\infty}$ , generated by Algorithm 3.2 converges strongly to  $x^* \in \Gamma$ , provided that  $\gamma \in (0, (1-\mu)/L)$  and  $\{\alpha_k\}_{k=0}^{\infty} \subset (\delta, 1-\beta-\delta)$  for small enough  $\delta > 0$ .

*Proof.* Let  $x^* \in \Gamma$  and choose  $x^0 \in \mathcal{H}_1$  such that

(3.7) 
$$\langle x^0 - x^*, \sigma \rangle > 0,$$

then there exists  $\epsilon > 0$  such that

(3.8) 
$$\langle x^0 - x^*, \sigma \rangle \ge \epsilon \|x^0 - x^*\|^2$$

We now prove by induction that

(3.9) 
$$\langle x^k - x^*, \sigma \rangle \ge \epsilon ||x^k - x^*||^2 \text{ for all } k \ge 0.$$

Assume it holds for k > 0,

$$\langle x^{k+1} - x^*, \sigma \rangle = \langle x^{k+1} - x^k + x^k - x^*, \sigma \rangle$$
  
=  $\langle x^{k+1} - x^k, \sigma \rangle + \langle x^k - x^*, \sigma \rangle$   
(3.10) =  $\gamma \langle A^*(T - I)Ax^k + \alpha_k(U(u^k) - u^k), \sigma \rangle + \langle x^k - x^*, \sigma \rangle.$ 

Since  $\gamma > 0$ ,  $\alpha_k > 0$  and by (3.6) we get

(3.11) 
$$\langle x^{k+1} - x^*, \sigma \rangle \ge \langle x^k - x^*, \sigma \rangle$$

by the induction assumption, we get that

(3.12) 
$$\langle x^{k+1} - x^*, \sigma \rangle \ge \epsilon \|x^k - x^*\|^2,$$

by [30, Lemma 2.1] the sequence  $\{x^k\}_{k=0}^{\infty}$ , generated by Algorithm 3.2 is Féjermonotone with respect to  $\Gamma$ , i.e., for all  $k \ge 0$ ,  $||x^{k+1} - x^*|| \le ||x^k - x^*||$ . So we get

(3.13) 
$$\langle x^{k+1} - x^*, \sigma \rangle \ge \epsilon ||x^{k+1} - x^*||^2,$$

therefore (3.9) holds for all  $k \ge 0$ . Finally, by Theorem 3.3  $x^k \rightharpoonup x^*$ , we get  $||x^k - x^*|| \to 0$ , which completes the proof.

3.2. The general split common fixed points problem. Now we employ a product space formulation similar to [21], originally due to Pierra [35], to derive and analyze a simultaneous algorithm for Problem 1.9. Let  $\Gamma$  be the solution set of Problem 1.9. Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces, we introduce the spaces  $\mathbf{V} = \mathcal{H}_1$  and  $\mathbf{W} = \mathcal{H}_1^p \times \mathcal{H}_2^r$ , where p and r are as in Problem 1.9. Define the following sets in the product spaces

(3.14) 
$$\tilde{C} := \mathcal{H}_1$$
 and

(3.15) 
$$\tilde{\boldsymbol{Q}} := \left(\prod_{i=1}^{p} \sqrt{\lambda_i} C_i\right) \times \left(\prod_{j=1}^{r} \sqrt{\beta_j} Q_j\right),$$

and the operator

(3.17)

(3.16) 
$$\mathbf{A} := \left(\sqrt{\lambda_1}I, \dots, \sqrt{\lambda_p}I, \sqrt{\beta_1}A_1^*, \dots, \sqrt{\beta_r}A_r^*\right)^*,$$

where  $\lambda_i > 0$ , for  $i = 1, \ldots, p$ , and  $\beta_j > 0$ , for  $j = 1, \ldots, r$ . Let  $\mathbf{y} = (y_1, \ldots, y_p, \ldots, y_{p+r}) \in \mathbf{W}$ , where  $y_1, \ldots, y_p \in \mathcal{H}_1$  and  $y_{p+1}, \ldots, y_{p+r} \in \mathcal{H}_2$ . Define the operator  $\mathbf{T} : \mathbf{W} \to \mathbf{W}$  by

$$\boldsymbol{T}(\boldsymbol{y}) = \boldsymbol{T}\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_{p+r} \end{pmatrix} = ((U_1(y_1)), (U_2(y_2)), \dots, (U_p(y_p))), (T_1(y_{p+1})), (T_2(y_{p+2})), \dots, (T_r(y_{p+r}))).$$

We have obtained a two operators split fixed points problem in the product space, with sets  $\tilde{C} = \mathcal{H}_1$ ,  $\tilde{Q} \subseteq W$ , the operator A, the identity operator  $I : \tilde{C} \to \tilde{C}$  and the operator  $T : W \to W$ . This problem can be solved using Algorithm 3.2. It is also easy to verify that the following equivalence holds

(3.18) 
$$x \in \Gamma$$
 if and only if  $Ax \in \tilde{Q}$ .

Therefore, we may apply Algorithm 3.2

(3.19) 
$$x^{k+1} = (1 - \alpha_k)(x^k + \gamma A^* (T - I)Ax^k) + \alpha_k I(x^k + \gamma A^* (T - I)Ax^k)$$
$$= x^k + \gamma A^* (T - I)Ax^k$$

to the problem (3.14)–(3.17) in order to obtain a solution of the original SCFPP. Observe that in this case Algorithm 3.2 and Algorithm 3.1 coincides. The translation of the iterative step (3.19) to the original spaces  $\mathcal{H}_1$  and  $\mathcal{H}_2$  is obvious by using the relation

(3.20) 
$$\boldsymbol{T}(\boldsymbol{A}\boldsymbol{x}) = \left(\sqrt{\lambda_1}U_1(\boldsymbol{x}), \dots, \sqrt{\lambda_p}U_p(\boldsymbol{x}), \sqrt{\beta_1}A_1T_1(\boldsymbol{x}), \dots, \sqrt{\beta_t}A_rT_r(\boldsymbol{x})\right)^*$$

and obtain the following algorithm,

# Algorithm 3.7.

**Initialization:** Select an arbitrary starting point  $x^0 \in \mathcal{H}_1$ . **Iterative step:** Given the current iterate  $x^k$ , compute

(3.21) 
$$x^{k+1} = x^k + \gamma \left( \sum_{i=1}^p \lambda_i \left( U_i(x^k) - x^k \right) + \sum_{j=1}^r \beta_j A_j^* (T_j - I) A_j x^k \right).$$

Here  $\gamma \in (0, (1 - \mu)/L)$ ,  $L = \sum_{i=1}^{p} \lambda_i + \sum_{j=1}^{r} \beta_j ||T_j||^2$  and  $\mu$  is the maximum demicontractivity constant of  $\{U_i\}_{i=1}^{p}$ .

The following convergence result follows from Theorem 3.6.

**Theorem 3.8.** Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces and let  $A : \mathcal{H}_1 \to \mathcal{H}_2$ be a linear bounded operator. Let  $U_i : \mathcal{H}_1 \to \mathcal{H}_1$ , i = 1, ..., p, and  $T_j : \mathcal{H}_2 \to \mathcal{H}_2$ , j = 1, ..., r be a demicontractive operators (with constants  $\beta$  and  $\mu$ ) with non-empty

Fix (U) = C and Fix (T) = Q. Assume that  $(U_i - I)$ , i = 1, ..., p and  $(T_j - I)$ , j = 1, ..., r, are demiclosed at 0 and there exists  $0 \neq \sigma \in \mathcal{H}_1$  such that

(3.22) 
$$\begin{cases} \langle U_i(y) - y, \sigma \rangle \leq 0 \text{ for all } y \in \mathcal{H}_1, \ i = 1, \dots, p \\ \langle A_j^*(T_j - I)A_jy, \sigma \rangle \leq 0 \text{ for all } y \in \mathcal{H}_1, \ j = 1, \dots, r. \end{cases}$$

If  $\Gamma \neq \emptyset$  then any sequence  $\{x^k\}_{k=0}^{\infty}$ , generated by Algorithm 3.7 converges strongly to  $x^* \in \Gamma$ , provided that  $\gamma \in (0, (1-\mu)/L)$ ,  $L = \sum_{i=1}^{p} \lambda_i + \sum_{j=1}^{r} \beta_j ||T_j||^2$  and  $\mu$  is the maximum demicontractivity constant of  $\{U_i\}_{i=1}^{p}$ .

*Proof.* Applying Theorems 3.3 and 3.6 to the two operators split fixed points problem in the product space setting with  $U = \mathbf{I} : \mathcal{H}_1 \to \mathcal{H}_1$ ,  $\operatorname{Fix}(U) = \tilde{\mathbf{C}}$  and  $T = \mathbf{T} : \mathbf{W} \to \mathbf{W}$ ,  $\operatorname{Fix}(T) = \tilde{\mathbf{Q}}$  the proof follows.

3.3. Firmly nonexpansive operators. In this subsection we wish to present an interesting special case of demicontractive operators, which is firmly nonexpansive operators and establish strong convergence theorem of algorithm Algorithm 3.2. Our analysis follows similar arguments from the proof of [1, Theorem 1.1], see also [29, Lemma 7].

**Lemma 3.9.** Let  $\mathcal{X}$  be a Banach space which is uniformly convex. If the operator  $S : \mathcal{X} \to \mathcal{X}$  is nonexpansive, odd and asymptotically regular, then for any  $x \in \mathcal{X}$ , the sequence  $\{S^k(x)\}_{k=1}^{\infty}$  converges strongly to a fixed point of S.

The next theorem is focus in a special case of Algorithm 3.2, in which  $\alpha_k \equiv 1$ , that is a Landweber-type operator, see [12]. The theorem's proof follows the same lines as in [12] and is given for the convenient of the reader.

**Theorem 3.10.** Let  $\mathcal{H}_1$  and  $\mathcal{H}_2$  be two real Hilbert spaces and let  $A : \mathcal{H}_1 \to \mathcal{H}_2$  be a linear bounded operator. Let  $U : \mathcal{H}_1 \to \mathcal{H}_1$  and  $T : \mathcal{H}_2 \to \mathcal{H}_2$  be odd and firmly nonexpansive operators with non-empty Fix (U) = C and Fix (T) = Q. If  $\Gamma \neq \emptyset$ and  $\gamma \in (0, 2/L)$ , where L is the spectral radius of the operator  $A^*A$ , then for any  $x^0 \in \mathcal{H}_1$  any sequence  $\{x^k\}_{k=0}^{\infty}$ , generated by Algorithm 3.2 with  $\alpha_k \equiv 1$ , i.e.,

(3.23) 
$$x^{k+1} = U\left(x^k - \gamma A^*(I-T)Ax^k\right),$$

converges strongly to  $x^* \in \Gamma$ .

*Proof.* First we prove that the operator  $A^*(T-I)A$  is 1/L-inverse strongly monotone. So

$$\begin{aligned} \|A^*(I-T)Ax - A^*(I-T)Ay\|^2 \\ &= \langle A^*((I-T)Ax - (I-T)Ay), A^*((I-T)Ax - (I-T)Ay) \rangle \\ &= \langle (I-T)Ax - (I-T)Ay, AA^*((I-T)Ax - (I-T)Ay) \rangle \\ &\leq L \|(I-T)Ax - (I-T)Ay\|^2. \end{aligned}$$

In addition

(3.24)

(3.25)  
$$\|(I-T)Ax - (I-T)Ay\|^{2} = \|(Ax - T(Ax) - (Ay - T(Ay))\|^{2}$$
$$= \|Ax - Ay\|^{2} + \|T(Ay) - T(Ax)\|^{2}$$
$$- 2\langle T(Ax) - T(Ay), Ax - Ay \rangle,$$

since T is firmly nonexpansive

(3.26)  $\langle T(Ax) - T(Ay), Ax - Ay \rangle \ge \|T(Ax) - T(Ay)\|^2.$ 

Combining the above inequalities yields,

$$||A^{*}(I-T)Ax - A^{*}(I-T)Ay||^{2} \leq L(||Ax - Ay||^{2} - ||T(Ax) - T(Ay)||^{2})$$
  
$$\leq L||Ax - Ay||^{2} = L\langle x - y, A^{*}A(x - y)\rangle$$
  
$$= L\langle A(x - y), A(x - y)\rangle = L\langle x - y, A^{*}A(x - y)\rangle$$
  
$$\leq L^{2}||x - y||^{2}.$$

So we get that the operator is L Lipschitz, i.e.,

(3.28) 
$$||A^*(I-T)Ax - A^*(I-T)Ay||^2 \le L^2 ||x-y||^2,$$

and it is easy to verify that it is 1/L-inverse strongly monotone. From now on we abbreviate  $G = A^*(I - T)A$ . Now we get that for  $\gamma \in (0, 2/L)$  the operator  $I - \gamma G$  is averaged (see e.g., [29, Lemma 3]). Since U is firmly nonexpansive, it is averaged and therefore the composition  $U(I - \gamma G)$ . By [29, Lemma 5],  $U(I - \gamma G)$  is strongly nonexpansive and as a result of [6, Corollary 1.1] it is asymptotically regular. Since T and U are odd then  $I - \gamma G$  and also the composition  $U(I - \gamma G)$ . Finally the strong convergence is obtained by [29, Lemma 7] and [21, Lemma 3.4].

# 4. Applications

In this section we compare our new SIP instance with a standard split convex feasibility modeling. While the standard SCFP modeling allow to obtain some solution, ours enable to find the projection of a given point onto the solution set. In order to motivate to this advantage we briefly recall the Intensity-Modulated Radiation Therapy (IMRT) in which, for example, the minimum solution of a SCFP is called least-intensity feasible solution, see Xiao et al. [38].

Intensity-modulated radiation therapy (IMRT) is an advanced mode of high-precision radiotherapy that uses computer-controlled linear accelerators to deliver precise radiation doses to a malignant tumor or specific areas within the tumor. The idea is that beamlets of radiation with different intensities are transmitted into the body of the patient. Each voxel within the patient will then absorb a certain dose of radiation from each beamlet. The goal is to allows higher radiation doses to be focused to regions within the tumor while minimizing the dose to surrounding normal critical structures.

Censor et al. see e.g., [15], showed how the IMRT treatment planning can be formulated as a split convex feasibility problem. The idea is to consider (by discretization) J beamlets and divide also the region of interest of the patient into Ivoxels. So, the problem consists of two spaces,  $\mathbb{R}^J$  - the radiation intensity space and  $\mathbb{R}^I$  - the dose space. Denote by  $x := (x_j)_{j=1}^J \in \mathbb{R}^J$  the vector of intensities and let  $d_{ij} \geq 0$  denotes the dose absorbed in voxel i due to radiation of unit intensity from the j-th beamlet. In order to present the linear transformation between the two spaces  $\mathbb{R}^J$  and  $\mathbb{R}^I$  we denote by  $h := (h_i)_{i=1}^I \in \mathbb{R}^I$  the dose vector, whose entries,  $h_i$  represent the total dose absorbed in voxel i, therefore

$$(4.1) h_i = \sum_{j=1}^J d_{ij} x_j$$

In each space there are several convex constraints sets, for example non-negativity of the intensities, that is

(4.2) 
$$\mathbb{R}^J_+ = \{ x \in \mathbb{R}^J \mid x_j \ge 0 \text{ for all } j \in J \}.$$

In the dose space typical constraints can be of the following nature. Let  $S_t$  be some volume of interest. In case that it represent an organ at risk, then it is natural to require that the dose should not exceed an upper bound  $U_t$ . This corresponds to the constraint set:

(4.3) 
$$Q_{max,t} = \{h \in \mathbb{R}^{I} \mid h_{i} \leq U_{t} \text{ for all } i \in S_{t}\}.$$

Similarly, if  $S_t$  is a tumor volume, the dose should not fall below a lower bound  $l_t$ and we can write the set

(4.4) 
$$Q_{\min,t} = \{h \in \mathbb{R}^I \mid h_i \ge l_t \text{ for all } i \in S_t\}.$$

There exists other kind of constraints sets but we our focus here is only in the above. Now it looks natural to search for the least-intensity feasible (LIF) solution of the above SCFP as in Xiao et al. paper [38].

4.1. Numerical example. In order to illustrate the performance and advantage of our proposed scheme, algorithm we compare the algorithm runs for a linear split feasibility problem taken from Dang and Xue [22]. It is worth mentioning again that our scheme allow to find the projection of a given point onto the solution set of the SCFP. All computations were performed using MATLAB R2015a on an Intel Core i5-4200U 2.3GHz running 64-bit Windows. The cpu time is measured in seconds using the intrinsic MATLAB function cputime. The exact solution of the problem (0.2645, -0.6568, 0.4890, -0.7548, -0.3836) is obtained by using Matlab built-in function fmincon. The first 89 iterations of our scheme are presented in Table 1, where the iteration's number 89 is taken from Dang and Xue [22] when the stopping criteria is achieved. We obtain and approximate solution after 89 iterations after 0.0781 seconds. In Figure 1 we present the quintiles (in blue) and median (in red) of the iteration's trajectories of Algorithm 3.7 for different choices of parameters  $\gamma$ ,  $\lambda_i$ , for  $1 \leq i \leq 2$ , and  $\beta_j$  for  $1 \leq j \leq 3$ . Let the Euclidean spaces  $\mathbb{R}^5$  and  $\mathbb{R}^4$  and consider the constraints sets

(4.5) 
$$C_1 = \{x \in \mathbb{R}^5 \mid x_1 + 2x_2 + x_3 + x_4 \le 5\}$$
$$C_2 = \{x \in \mathbb{R}^5 \mid x_2 + 4x_4 + 4x_5 \le 1\}$$

and

(4.6)  

$$Q_{1} = \{y \in \mathbb{R}^{4} \mid y_{1} + y_{4} \leq 1\}$$

$$Q_{2} = \{y \in \mathbb{R}^{4} \mid 2y_{2} + 3y_{3} \leq 6\}$$

$$Q_{3} = \{y \in \mathbb{R}^{4} \mid y_{3} + 2y_{4} \leq 10\}$$

In addition

(4.7) 
$$A = \begin{pmatrix} 2 & -1 & 3 & 2 & 3 \\ 1 & 2 & 5 & 2 & 1 \\ 2 & 0 & 2 & 1 & -2 \\ 2 & -1 & 0 & -3 & 5 \end{pmatrix}.$$

Given this data Dang and Xue considered the following SCFP

(4.8) find a point 
$$x^* \in \bigcap_{i=1}^2 C_i$$
  
and such that

and such that

the point  $y^* = Ax^* \cap_{i=1}^3 Q_i$ . (4.9)

They compared their scheme with Censor et al. method [18] which is Algorithm 3.7). Our SIP problem enable us to solve a more general problem, for example best approximation problem is obtained if  $IP_1$  is variational inequality and  $IP_2$  is feasibility problem. So, for a given point  $p \in \mathbb{R}^5$  we wish to solve

(4.10) 
$$\min f(x) := \frac{1}{2} ||x - p||^2$$
such that x solves (4.8)-(4.9)

We take p = (1, -1, 1, -1, 1) as  $x^0$  in [22]. We also choose  $U_i = P_{C_i} (I - \lambda (I - p))$ for positive  $\lambda$  and i = 1, 2 (this choice is due to the fact that  $\nabla \left(\frac{1}{2} \|x - p\|^2\right) = I - p$ ). Moreover  $T_j = P_{Q_j}$  for positive j = 1, 2, 3 and  $A_j = A$ . For simplicity we take  $\lambda_i = 1, \beta_j = 1, \gamma = 0.1$ . So the iterative step of our scheme translates to the following (4.11)

$$x^{k+1} = x^k + 0.1 \left( \sum_{i=1}^2 \left( P_{C_i} \left( \frac{x^k + p}{2} \right) - x^k \right) + \sum_{j=1}^3 A^t \left( P_{Q_j} \left( Ax^k \right) - Ax^k \right) \right).$$



FIGURE 1. The quintiles (in blue) and median (in red) of the iteration's trajectories calculated via (4.11) for different choices of  $\gamma$ ,  $\lambda_i$ , for  $1 \leq i \leq 2$ , and  $\beta_j$  for  $1 \leq j \leq 3$ .

Iterations	$x_1$	$x_2$	$x_3$	$x_4$	$x_5$
1	1	-1	1	-1	1
2	0.9489	-0.9788	0.9658	-0.98	0.9117
3	0.90177426	-0.95898452	0.9344442	-0.9614787	0.82964858
4	0.85832628	-0.940456015	0.905712211	-0.944333172	0.753390518
5	0.818281537	-0.923123976	0.879399031	-0.928467843	0.682503979
6	0.781385862	-0.906904421	0.855315995	-0.913793957	0.616598063
:	:	•	:	•	:
40	0.300783969	-0.675872355	0.517753296	-0.761538378	-0.307677191
:	:	•	:	•	:
89	0.264826996	-0.656992447	0.48929388	-0.754801155	-0.382801781

TABLE 1. The first 89 coordinate wise iterations generated by the iterative step (4.11).

#### 5. Acknowledgments

We thank the anonymous referee for the thorough review and appreciate the comments and suggestions, which help improving the quality of this paper.

### References

- J.-B. Baillon, R. E. Bruck and S. Reich, On the asymptotic behavior of nonexpansive mappings and semigroups in Banach spaces, Houston J. Math. 4 (1978), 1–9.
- [2] H. H. Bauschke and P. L. Combettes, A weak-to-strong convergence principle for Fejérmonotone methods in Hilbert spaces, Math. Oper. Res. 26 (2001), 248–264.
- [3] H. H. Bauschke, E. Matoušková, S. Reich, Projection and proximal point methods: convergence results and counterexamples, Nonlinear Anal. 56 (2004), 715–738.
- [4] F. E. Browder, Convergence theorems for sequences of nonlinear operators in Banach spaces, Math. Z. 100 (1967), 201–225.
- [5] F. E. Browder and W. V. Petryshyn, Construction of fixed points of nonlinear mappings in Hilbert space, J. Math. Anal. Appl. 20 (1967), 297–228.
- [6] R. E. Bruck and S. Reich, Nonexpansive projections and resolvents of accretive operators in Banach spaces, Houston J. Math. 3 (1977), 459–470.
- [7] C. L. Byrne, Iterative projection onto convex sets using multiple Bregman distances, Inverse Probl. 15 (1999), 1295–1313.
- [8] C. Byrne, Iterative oblique projection onto convex sets and the split feasibility problem, Inverse Probl. 18 (2002), 441–453.
- [9] C. Byrne, A unified treatment of some iterative algorithms in signal processing and image reconstruction, Inverse Probl. **20** (2004), 103–120.
- [10] C. Byrne, Y. Censor, A. Gibali and S. Reich, *The split common null point problem*, J. Nonlinear Convex Anal. **13** (2012), 759–775.
- [11] A. Cegielski, Generalized relaxations of nonexpansive operators and convex feasibility problems, Contem. Math. 513 (2010), 111–123.
- [12] A. Cegielski, Landweber-type operator and its properties, Contem. Math. 658 (2016), 139–148.
- [13] A. Cegielski, Y. Censor, Opial-type theorems and the common fixed point problem, Fixed-Point Algorithms for Inverse Problems in Science and Engineering, Editors: H. H. Bauschke, R. S. Burachik, P. L. Combettes, V. Elser, D. R. Luke, H. Wolkowicz, Springer Optimization and Its Applications 49, Springer, New York, 2011, 155–183.

- [14] Y. Censor, M. D. Altschuler and W. D. Powlis, On the use of Cimmino's simultaneous projections method for computing a solution of the inverse problem in radiation therapy treatment planning, Inverse Probl. 4 (1988), 607–623.
- [15] Y. Censor, T. Bortfeld, B. Martin and A. Trofimov, A unified approach for inversion problems in intensity-modulated radiation therapy, Phys. Med. Biol. 51 (2006), 2353–2365.
- [16] Y. Censor, R. Davidi and G. T. Herman, Perturbation resilience and superiorization of iterative algorithms, Inverse Probl. 26 (2010), 065008 (pp. 17).
- [17] Y. Censor and T. Elfving, A multiprojection algorithm using Bregman projections in a product space, Numer. Algorithms 8 (1994), 221–239.
- [18] Y. Censor, T. Elfving, N. Kopf and T. Bortfeld, The multiple-sets split feasibility problem and its applications for inverse problems, Inverse Probl. 21 (2005), 2071–2084.
- [19] Y. Censor, A. Gibali and S. Reich, Algorithms for the split variational inequality problem, Numer. Algorithms 59 (2012), 301–323.
- [20] Y. Censor, A. Segal, On the string averaging method for sparse common fixed point problems, Int. Trans. Oper. Res. 16 (2009), 481–494.
- [21] Y. Censor and A. Segal, The split common fixed point problem for directed operators, J. Convex Anal. 16 (2009), 587–600.
- [22] Y. Dang and Z. Xue, Iterative process for solving a multiple-set split feasibility problem, J. Inequal. Appl. (2015), 2015:47.
- [23] A. Genel and J. Lindenstrauss, An example concerning fixed points, Israel J. Math. 22 (1975), 81–85.
- [24] A. Gibali, K.-H. Küfer, P. Süss, Reformulating the Pascoletti-Serafini problem as a bi-level optimization problem, Contemp. Math. 636 (2015), 121–129.
- [25] T. L. Hicks and J. R. Kubicek, On the Mann iteration process in Hilbert space, J. Math. Anal. Appl. 59 (1977), 498–504.
- [26] Şt. Măruşter, The solution by iteration of nonlinear evations in Hilbert spaces, Proc. Amer. Math. Soc. 63 (1977), 69–73.
- [27] Şt. Măruşter, Quasi-nonexpansivity and the convex feasibility problem, An. Ştiinţ. Univ. Al. I. Cuza Iaşi. Mat. (N.S.) 15 (2005), 47–56.
- [28] Şt. Măruşter, and C. Popirlan, On the Mann-type iteration and convex feasibility problem, J. Comput. Appl. Math. 212 (2008), 390–396.
- [29] E. Masad and S. Reich, A note on the multiple-set split convex feasibility problem in Hilbert space, J. Non. Con. Anal. 8 (2007), 367–371.
- [30] A. Moudafi, The split common fixed point problem for demicontractive mappings, Inverse Probl. 26 (2010), 587–600.
- [31] A. Moudafi, Split monotone variational inclusions, J. Optim. Theory Appl. 150 (2011), 275– 283.
- [32] M. O. Osilike and A. Udomene, Demiclosedness principle and convergence theorems for stictly pseudocontractive mappings of the Browder-Petryshyn type, J. Math. Anal. Appl. 256 (2001), 431–445.
- [33] Z. Opial, Weak convergence of the sequence of successive approximations for nonexpansive mappings, Bull. Amer. Math. Soc. 73 (1967), 591–597.
- [34] W. V. Petryshyn and T. E. Williamson, Strong and weak convergence of the sequence of successaive approximations for quasi-nonexpansive mappings, J. Math. Anal. Appl. 43 (1973), 459–497.
- [35] G. Pierra, Decomposition through formalization in a product space, Math. Program. 28 (1984), 96–115.
- [36] A. Segal, Directed Operators for Common Fixed Point Problems and Convex Programming Problems, PhD Thesis, University of Haifa, Haifa, Israel, 2008.
- [37] H. F. Senter and W. G. Dotson, Approximating fixed points of nonexpansive mappings, Proc. Amer. Math. Soc. 44 (1974), 375–380.
- [38] Y. Xiao, Y. Censor, D. Michalski and J.M. Galvin, The least-intensity feasible solution for aperture-based inverse planning in radiation therapy, Ann. Oper. Res. 119 (2003), 183–203.

- [39] I. Yamada, The hybrid steepest descent method for the variational inequality problem over the intersection of fixed point sets of nonexpansive mappings, Inherently Parallel Algorithms in Feasibility and Optimization and their Applications, Editors: D. Butnariu, Y. Censor, S. Reich, Elsevier, Amsterdam, 2001, 473–504.
- [40] I. Yamada, N. Ogura, Hybrid steepest descent method for variational inequality problem over the fixed point set of certain quasi-nonexpansive mappings, Numer. Funct. Anal. Optim. 25 (2004), 619–655.
- [41] M. Yukawa, K. Slavakis, and I. Yamada, Multi-domain adaptive filtering by feasibility spliting, ICASSP (2010), 3814–3817.
- [42] M. Zaknoon, Algorithmic Developments for the Convex Feasibility Problem, PhD Thesis, University of Haifa, Haifa, Israel, 2003.

Manuscript received May 24 2016 revised July 14 2016

A. GIBALI

Department of Mathematics, ORT Braude College, Karmiel 2161002, Israel *E-mail address:* avivg@braude.ac.il