We consider the composite variational inequality in the form:

Find 
$$x^* \in \mathbb{R}^d : R(x^*) = 0$$
 with  $R(x) := Q(x) + P(x)$ , (1)

where  $Q(x), P(x) : \mathbb{R}^d \to \mathbb{R}^d$ .

**Assumption 1.** R(x) satisfies minty assumption:

$$\exists x^* \in \mathbb{R}^d : \forall x \in \mathbb{R}^d \hookrightarrow \langle R(x), x - x^* \rangle \ge 0.$$

**Assumption 2.** Q(x) is  $L_q$ -Lipschitz:

$$\forall x_1, x_2 \in \mathbb{R}^d \hookrightarrow ||Q(x_1) - Q(x_2)|| \le L_q ||x_1 - x_2||.$$

**Assumption 3.** P(x) is  $L_p$ -Lipschitz:

$$\forall x_1, x_2 \in \mathbb{R}^d \hookrightarrow ||P(x_1) - P(x_2)|| \le L_p ||x_1 - x_2||.$$

## Algorithm 1 Extragradient Sliding

- 1: Input:  $x^0 \in \mathbb{R}^d$
- 2: Parameters:  $\eta, \theta > 0, K \in \mathbb{N}$

3: **for** 
$$k=0,1,2,\ldots,K-1$$
 **do**
4: Find  $u^k \approx \tilde{u}^k$  where  $\tilde{u}^k$  is solution for Find  $\tilde{u}^k \in \mathbb{R}^d : B_{\theta}^k(\tilde{u}^k) = 0$  with  $B_{\theta}^k(x) := P(x^k) + Q(x) + \frac{1}{\theta}(x - x^k)$ 

- 6: end for
- 7: Output:  $x^K$

**Theorem 1.** Consider Algorithm 1 for Problem 1 under Assumptions 1, 2, 3, with the following tuning:

$$\theta = \frac{1}{2L_p}, \eta = \frac{\theta}{4}.$$
 (2)

Assume that  $u^k$  (line 4) satisfies:

$$||B_{\theta}^{k}(u^{k})||^{2} \le \frac{L_{p}^{2}}{3}||x^{k} - \tilde{u}^{k}||^{2}. \tag{3}$$

Then, we have the following inequality:

$$\min_{0 \le j \le K-1} ||R(u^j)||^2 \le \frac{16L_p^2 ||x_0 - x^*||^2}{K}.$$
 (4)

Inequality 4 means sublinear convergence in non-convex non-concave case.

**Lemma 1.** Consider Algorithm 1. Let  $\theta$  be defined as  $\theta = \frac{1}{2L_p}$ . Then, under Assumptions 1, 2, 3, the following inequality holds:

$$2\langle x^* - x^k, R(u^k) \rangle \le -\theta ||R(u^k)||^2 + 3\theta \left( ||B_{\theta}^k(u^k)||^2 - \frac{L_p^2}{3} ||x^k - \tilde{u}^k||^2 \right). \tag{5}$$

## **Proof of Lemma 1.**

Using Minty assumption 3, we get

$$\begin{array}{lcl} 2\langle x^k-x^*,R(u^k)\rangle & = & 2\langle x^*-u^k,R(u^k)\rangle + 2\langle u^k-x^k,R(u^k)\rangle \\ & \leq & 2\langle u^k-x^k,R(u^k)\rangle = 2\theta\left\langle \frac{1}{\theta}(u^k-x^k),R(u^k)\right\rangle \end{array}$$

The definition of  $B_{\theta}^{k}(x)$  (line 4) gives

$$2\theta \left\langle \frac{1}{\theta}(u^k - x^k), R(u^k) \right\rangle = \theta \left\| \frac{1}{\theta}(u^k - x^k) + R(u^k) \right\|^2 - \frac{1}{\theta}||u^k - x^k||^2 - \theta||R(u^k)||^2$$
$$= -\frac{1}{\theta}||u^k - x^k||^2 - \theta||R(u^k)||^2 + \theta||B_{\theta}^k(u^k) - P(x^k) + P(u^k)||^2.$$

Using of Cauchy–Bunyakovsky–Schwarz inequality and  $L_p$ -Lipschitzness of P(x), we get

$$\begin{aligned} 2\langle x^k - x^*, R(u^k) \rangle & \leq & -\frac{1}{\theta} \|u^k - x^k\| - \theta \|R(u^k)\|^2 + 2\theta \|B_{\theta}^k(u^k)\|^2 + 2\|P(u^k) - P(x^k)\|^2 \\ & \leq & -\frac{1}{\theta} \|u^k - x^k\| - \theta \|R(u^k)\|^2 + 2\theta \|B_{\theta}^k(u^k)\|^2 + 2\theta L_p^2 \|u^k - x^k\|^2 \\ & = & -\frac{1}{\theta} \left(1 - 2\theta^2 L_p^2\right) \|u^k - x^k\|^2 - \theta \|R(u^k)\|^2 + 2\theta \|B_{\theta}^k(u^k)\|^2. \end{aligned}$$

With  $\theta=\frac{1}{2L_p}$  and CBS inequality in the form  $-\|a\|^2\leq \|b\|^2-\frac{1}{2}\|a+b\|^2$ , we have:

$$2\langle x^* - x^k, R(u^k) \rangle \leq -\theta \|R(u^k)\|^2 + 2\theta \|B_{\theta}^k(u^k)\|^2 - \frac{1}{2\theta} \|u^k - x^k\|^2$$
$$\leq -\theta \|R(u^k)\|^2 + 2\theta \|B_{\theta}^k(u^k)\|^2 + \frac{1}{2\theta} \|u^k - \tilde{u}^k\|^2 - \frac{1}{4\theta} \|x^k - \tilde{u}^k\|^2.$$

One can observe that  $B^k_{\theta}(x)$  is  $\frac{1}{\theta}-$  strongly monotone. It gives that

$$\frac{1}{\theta} \|x - y\|^2 \le \langle B_{\theta}^k(x) - B_{\theta}^k(y), x - y \rangle \le \|B_{\theta}^k(x) - B_{\theta}^k(y)\|^2 \|x - y\|^2.$$

With  $B_{\theta}^{k}(\tilde{u}^{k}) = 0$  ( $\tilde{u}^{k}$  is the solution of line 4), we get

$$\frac{1}{2\theta^2} \|u^k - \tilde{u}^k\|^2 \le \frac{1}{2} \|B_{\theta}^k(u^k)\|^2.$$

Applying this to the upper inequality, we finalize the proof:

$$\begin{aligned} 2\langle x^* - x^k, R(u^k) \rangle & \leq & -\theta \|R(u^k)\|^2 + \frac{5}{2}\theta \|B_{\theta}^k(u^k)\|^2 - \frac{1}{4\theta} \|x^k - \tilde{u}^k\|^2 \\ & \leq & -\theta \|R(u^k)\|^2 + 3\theta \|B_{\theta}^k(u^k)\|^2 - \frac{3\theta}{12\theta^2} \|x^k - \tilde{u}^k\|^2 \\ & = & -\theta \|R(u^k)\|^2 + 3\theta \left( \|B_{\theta}^k(u^k)\|^2 - \frac{L_p^2}{3} \|x^k - \tilde{u}^k\|^2 \right). \end{aligned}$$

## **Proof of Theorem 1.**

Line 5 of Algorithm 1 gives

$$\begin{aligned} \|x^{k+1} - x^*\|^2 &= \|x^{k+1} - x^k\|^2 + 2\langle x^{k+1} - x^k, x^k - x^* \rangle + \|x^k - x^*\|^2 \\ &= \|x^{k+1} - x^k\|^2 + \|x^k - x^*\|^2 - 2\eta\langle R(u^k), x^k - x^* \rangle \end{aligned}$$

Using the Lemma 1 and assumption on the norm  $\|B_{\theta}^k(u^k)\|^2$  3, we get

$$||x^{k+1} - x^*||^2 \le ||x^{k+1} - x^k||^2 + ||x^k - x^*||^2 - \eta\theta ||R(u^k)||^2 + 3\eta\theta \left( ||B_{\theta}^k(u^k)||^2 - \frac{L_p^2}{3} ||x^k - \tilde{u}^k||^2 \right)$$

$$\le ||x^{k+1} - x^k||^2 + ||x^k - x^*||^2 - \eta\theta ||R(u^k)||^2.$$

From line 5 it follows:

$$\|x^{k+1} - x^*\|^2 \quad \leq \quad \eta^2 \|R(u^k)\|^2 + \|x^k - x^*\|^2 - \eta\theta \|R(u^k)\|^2.$$

Let us substitute  $\theta = \frac{1}{2L_p}, \eta = \frac{\theta}{2}$ :

$$\begin{aligned} \|x^{k+1} - x^*\|^2 & \leq & \|x^k - x^*\|^2 - \eta(\theta - \eta) \|R(u^k)\|^2 \\ & \leq & \|x^k - x^*\|^2 - \frac{\theta^2}{4} \|R(u^k)\|^2. \end{aligned}$$

Summing from 1 to K-1, we get

$$\sum_{j=0}^{K-1} \frac{\theta^2}{4} \|R(u^j)\|^2 \le \sum_{j=0}^{K-1} (\|x^j - x^*\|^2 - \|x^{j+1} - x^*\|^2)$$

$$= \|x^0 - x^*\|^2 - \|x^K - x^*\|^2 \le \|x^0 - x^*\|^2.$$

Thus we have:

$$\sum_{j=0}^{K-1} ||R(u^j)||^2 \le 16L_p^2 ||x^0 - x^*||^2.$$

And finally we get:

$$\min_{0 \leq j \leq K-1} \lvert \lvert R(u^j) \rvert \rvert^2 \leq \frac{16 L_p^2 \|x^0 - x^*\|^2}{K}.$$