

# Entropic Bundle Algorithms

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## Abstract

Several methods have been used to calculate an approximate critical point of a nonsmooth convex function, in particular the proximal point method and the bundle method. In this paper we propose a class of methods, obtained by combining the bundle method with the entropic distances. In our analysis, the convergence properties obtained cover the convergence results of the bundle method, while giving other.

**Key words :** nonsmooth optimization , bundle method , proximal point , entropic distance.

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## 1. INTRODUCTION

Let's consider the problem of convex optimization defined by :

$$(P) : \min \{ f(x), x \in R^d \}$$

Several numerical methods have been used to resolve (P) , especially the methods of the proximal point see [1, 3, 5, 7, 9, 10, 11, 15, 16] and the methods of bundle studied by several authors [8, 12, 13, 14] . The pinciple of these is based of the approximaion of f by a function's sequence  $\varphi^k$  normally more simple than f. The principle restriction of these methods is that the function f is at finite values. By coupling the methods of bundle with the entropic distances [2] definid by

$$D_h(x, y) := h(x) - h(y) - \langle x - y, \nabla h(y) \rangle,$$

we propose a class of methods (EBA) called Entropic Bundle Algorithms . These, in contrary the bundle methods (BM) , allowing to solve (P) when f verifies:

$$(A_1) : \quad f = F + \Psi_{\bar{S}},$$

where S is the function zone of Bregman h and F is a convex function at finite values .

In particular , by choosing  $h_1(x) = \sum_{i=1}^{i=d} x_i \log x_i - x_i$  , these methods allow to minimize F on the positive cone of  $R^d$  . For  $h_0(x) = \frac{1}{2} \| x \|^2$  , we find the bundle method (BM) described by C. Lemarechal and R.Correa [13].

Our notation is fairly standart ,  $\langle \cdot, \cdot \rangle$  is the scalar product on  $R^d$  , and the associated norm  $\| \cdot \|$  . The closure of the set C ( relative interior) is denoted by  $\bar{C}$  ( riC, respectively),  $\text{Adh} \{x^k\}$  is the set of adherence values of a sequence  $\{x^k\}$ . For any convex function f , we denote by :

- (1)  $\text{dom} f = \{x \in R^d, f(x) < +\infty\}$  its effective domain,
- (2)  $\partial_\epsilon f(\cdot) = \{v, f(y) \geq f(\cdot) + \langle v, y - \cdot \rangle - \epsilon, \forall y\}$  its  $\epsilon$  - *subdifferential*,
- (3)  $\text{arg min} f = \{x \in R^d, f(x) = \inf f\}$  its *argmin* f,
- (4)  $\epsilon - \text{arg min} f = \{x \in R^d, f(x) \leq \inf f + \epsilon\}$  its  $\epsilon$  - *argmin* f.

## 2. PRELIMIMARIE

In this section, we remind some theoretical properties of entropic approximations studied by Kabbadj in [6]. These results are necessary for the analysis of the methods proposed in section 3 and 4 .

Let S be an convex open subset of  $R^d$  and  $h : \bar{S} \rightarrow R$ . We define  $D_h(\cdot, \cdot)$  by :  $\forall x \in \bar{S}, \forall y \in S :$

$$D_h(x, y) := h(x) - h(y) - \langle x - y, \nabla h(y) \rangle .$$

Let us consider the following hypotheses :

$H_1$  : h is continuously differentiable on S.

$H_2$  : h is continuous and strictly convex on  $\bar{S}$ .

$H_3$  :  $\forall r \geq 0, \forall x \in \bar{S}, \forall y \in S$ , the sets  $L_1(x, r)$  and  $L_2(y, r)$  are bounded where

$$L_1(x, r) = \{y \in S / D_h(x, y) \leq r\}$$

$$L_2(y, r) = \{x \in \bar{S} / D_h(x, y) \leq r\}.$$

$H_4$  : If  $\{y^k\}_k \subset S$  is such as  $y^k \rightarrow y^* \in \bar{S}$ , so  $D_h(y^*, y^k) \rightarrow 0$ .

$H_5$  : If  $\{x^k\}_k$  and  $\{y^k\}_k$  are two sequences of  $S$  such as :  $D_h(x^k, y^k) \rightarrow 0$  and

$$x^k \rightarrow x^* \in S, \text{ then } y^k \rightarrow x^*.$$

**Definition 2.1.**

(i)  $h : \bar{S} \rightarrow R$  is a Bregman function on  $S$  or " D-function" if  $h$  verify  $H_1, H_2, H_3, H_4$  and  $H_5$ .

(ii)  $D_h(., .)$ , is called entropic distance if  $h$  is a Bregman function.

We put :

$$A(S) = \{h : \bar{S} \rightarrow R \text{ verifying } H_1 \text{ and } H_2\}$$

$$B(S) = \{h : \bar{S} \rightarrow R \text{ verifying } H_1, H_2, H_3, H_4 \text{ and } H_5\}.$$

$$\Gamma_0(R^d) = \{f : R^d \rightarrow R \cup \{+\infty\} \text{ proper, closed and convex}\}$$

**Lemma 2.2.**  $\forall h \in A(S), \forall a \in \bar{S}, \forall b, c \in S$ :

$$D_h(a, b) + D_h(b, c) - D_h(a, c) = \langle a - b, \nabla h(c) - \nabla h(b) \rangle .$$

$D_h(., .)$  is not a distance because the properties of the symmetry and the triangle inequality are not verified, however positivity is ensured by the proposition below.

**Proposition 2.3.** If  $h \in A(S)$ , then :

$$D_h(x, y) = \begin{cases} 0 & \text{if } x = y, \\ > 0 & \text{if } x \neq y \end{cases}$$

**Theorem 2.4.** [6] Let  $f \in \Gamma_0(R^d)$  and  $h \in A(S)$  such as  $\text{dom} f \cap \bar{S} \neq \emptyset$ . If one of the two following conditions are verified :

$$(i) \inf_{\bar{S}} f > -\infty \text{ and } h \text{ verify } H_3$$

$$(ii) \text{Im} \nabla h = R^d.$$

Then for all  $x \in S$ , for all  $\lambda > 0$ , the function  $u \mapsto f(u) + \lambda^{-1}D_h(u, v)$  has a unique minimum point on  $\overline{S}$ .

**Definitions 2.5.**  $f$  and  $h$  verify the hypothesis of the Theorem 2.4.

i) The entropic approximation of  $f$  compared to  $h$ , of parameter  $\lambda (\lambda > 0)$  is the function defined by :

$$f_{h\lambda}(x) := \inf_{y \in \overline{S}} \{f(y) + \lambda^{-1}D_h(y, x)\}, \forall x \in S.$$

ii) The application entropic proximal of  $f$  comparing to  $h$ , of parameter  $\lambda$  is the operator defined by :

$$h_\lambda^f(x) := prox_{\lambda f}^h(x) := \arg \min_{y \in \overline{S}} \{f(y) + \lambda^{-1}D_h(y, x)\}, \forall x \in S.$$

**Proposition 2.6.** [6] Let  $h \in A(S)$  and  $f \in \Gamma_0(R^d)$  such as :

- (a)  $ri(\text{dom } f) \cap S \neq \phi$ ,
- (b)  $Im \nabla h = R^d$ .

Then :  $\forall x \in S, \forall \lambda > 0$

$$h_\lambda^f(x) \in S \tag{1}$$

$$\frac{\nabla h(x) - \nabla h(h_\lambda^f(x))}{\lambda} \in \partial f(h_\lambda^f(x)) \tag{2}$$

Some examples of Bregman functions are given below.

**Example 2.7.** If  $S_0 = R^d$  and  $h_0(x) = \frac{1}{2} \|x\|^2$  then

$$D_{h_0}(x, y) = \frac{1}{2} \|x - y\|^2.$$

**Example 2.8.** If  $S_1 = R_{++}^d := \{x \in R^d / x_i > 0, i = 1, \dots, d\}$  and

$$h_1(x) = \sum_{i=1}^{i=d} x_i \log x_i - x_i ; \forall x \in \overline{S_1},$$

with the convention :  $0 \log 0 = 0$  , then

$$D_{h_1}(x, y) = \sum_{i=1}^d x_i \log \frac{x_i}{y_i} + y_i - x_i, \forall (x, y) \in \overline{S_1} X S_1.$$

**Example 2.9.** If  $S_2 = ]-1, 1[^d$  and  $h_2(x) = -\sum_{i=1}^d \sqrt{1 - x_i^2}$  , then:

$$D_{h_2}(x, y) = h_2(x) + \sum_{i=1}^d \frac{1 - x_i y_i}{\sqrt{1 - y_i^2}}, \forall (x, y) \in \overline{S_2} X S_2.$$

We easily verifies that

$$h_i \in B(S_i), i = 0, 1, 2.$$

### 3. MAIN RESULTS

In this section, we analyze an algorithm that plays a decisive role in establishing the convergence of the Entropic Bundle Algorithms proposed in section 4 , we suggest that  $h$  and  $f$  satisfy the following hypotheses

#### Assumptions A :

- (i)  $h \in B(S)$  such that  $Im \nabla h = R^d$
- (ii)  $f \in \Gamma_0(R^d)$  such that  $S \cap ri(dom f) \neq \emptyset$

#### Algorithm 1: Inexact Entropic Proximal (IEP)

- 1: input:  $x^0 \in S \cap ri(dom f)$
  - 2: for  $n = 1, 2, \dots$  with  $\lambda_n > 0$ , find  $x^n \in S$  and  $\varepsilon_n \geq 0$  such that  $f(x^n) \leq f(x^{n-1})$
- and

$$\frac{\nabla h(x^{n-1}) - \nabla h(x^n)}{\lambda_n} \in \partial_{\varepsilon_n} f(x^n)$$

**Proposition 3.1.** The sequence  $\{x^n\}_n$  defined by (IEP) exists and verified for all  $n \in N^*$  :

$$x^n \in \varepsilon_n - \operatorname{argmin}\{f(u) + \frac{1}{\lambda_n}D_h(u, x^{n-1}), u \in \bar{S}\}.$$

Proof. Existence: is deduced trivially from (2).

$$\Omega^n := \frac{\nabla h(x^{n-1}) - \nabla h(x^n)}{\lambda_n} \in \partial_{\varepsilon_n} f(x^n)$$

$\Rightarrow f(u) \geq f(x^n) + \langle u - x^n, \Omega^n \rangle - \varepsilon_n$ . By applying the Lemma 2.2., we have :

$$f(u) \geq f(x^n) + \lambda_n^{-1}[D_{h_n}(u, x^n) + D_{h_n}(x^n, x^{n-1}) - D_{h_n}(u, x^{n-1})] - \varepsilon_n \quad (3)$$

$\Rightarrow f(x^n) + \lambda_n^{-1}D_{h_n}(x^n, x^{n-1}) \leq f(u) + \lambda_n^{-1}D_{h_n}(u, x^{n-1}) + \varepsilon_n, \forall u \in \bar{S}$

$\Rightarrow x^n \in \varepsilon_n - \operatorname{argmin}\{f(u) + \frac{1}{\lambda_n}D_h(u, x^{n-1}), u \in \bar{S}\}$ . □

**Remark 3.2.** For  $\varepsilon_n = 0, \forall n \in N^*$  the algorithm (IEP) is written :

$$x^n = \operatorname{argmin}\{f(u) + \frac{1}{\lambda_n}D_h(u, x^{n-1}), u \in \bar{S}\},$$

which have nothing but the entropic proximal algorithm (EP) studied by [4, 18] . (IEP) is then an inexact version of the algorithm (EP) . The convergence results developed below cover the convergence properties given in [18] .

**Proposition 3.3.** (Summability) If  $f^* := \inf_{y \in \bar{S}} f(y) > -\infty, \sum_{n=1}^{\infty} \lambda_n \varepsilon_n < +\infty$  and  $0 < \lambda_n \leq \bar{\lambda}$ , then,

$$\sum_{n=1}^{\infty} D_h(x^n, x^{n-1}) < +\infty \text{ and } \sum_{n=1}^{\infty} D_h(x^{n-1}, x^n) < +\infty$$

Proof. From (3) , we have :

$$\lambda_n(f(x^n) - f(u)) \leq [D_h(u, x^{n-1}) - D_h(u, x^n) - D_h(x^n, x^{n-1})] + \varepsilon_n \lambda_n \quad (4)$$

Put  $u = x^{n-1}$  in (4), we have

$$D_h(x^n, x^{n-1}) + D_h(x^{n-1}, x^n) \leq \bar{\lambda}(f(x^{n-1}) - f(x^n)) + \lambda_n \varepsilon_n \quad (5)$$

$$\begin{aligned} &\Rightarrow \sum_{\substack{n=1 \\ n=p}}^{n=p} D_h(x^n, x^{n-1}) + D_h(x^{n-1}, x^n) \leq \bar{\lambda} \sum_{n=1}^{n=p} (f(x^{n-1}) - f(x^n)) + \sum_{n=1}^{n=p} \lambda_n \varepsilon_n \\ &\Rightarrow \sum_{n=1}^{n=p} D_h(x^n, x^{n-1}) + D_h(x^{n-1}, x^n) \leq \bar{\lambda}(f(x^0) - f^*) + \sum_{n=1}^{n=p} \lambda_n \varepsilon_n. \\ &\sum_{n=1}^{\infty} \lambda_n \varepsilon_n < +\infty \Rightarrow \sum_{n=1}^{\infty} D_h(x^n, x^{n-1}) < +\infty \text{ and } \sum_{n=1}^{\infty} D_h(x^{n-1}, x^n) < +\infty. \quad \square \end{aligned}$$

**Proposition 3.4.** (Global estimate in function values)

We suppose that  $\arg \min_{\bar{S}} f \neq \emptyset$ . Let  $t_p := \sum_{n=1}^p \lambda_n$ .

(a)  $\forall u \in \bar{S}, \forall p \in N^*, \text{ for } x^* \in \arg \min_{\bar{S}} f$

$$f(x^p) - f^* \leq \frac{1}{t_p} [D_h(x^*, x^0) + \sum_{n=1}^{\infty} \lambda_n \varepsilon_n] \tag{6}$$

(b) If  $\lambda_n = \lambda, \forall n \in N^*$ ,

$$f(x^p) - f^* = O\left(\frac{1}{p}\right) \tag{7}$$

Proof. (a) We have :

$$\lambda_n(f(x^n) - f(u)) \leq D_h(u, x^{n-1}) - D_h(u, x^n) + \varepsilon_n \lambda_n \tag{8}$$

$$\begin{aligned} &\Rightarrow \sum_{\substack{n=1 \\ n=p}}^{n=p} \lambda_n(f(x^n) - f(u)) \leq \sum_{n=1}^{n=p} D_h(u, x^{n-1}) - D_h(u, x^n) + \sum_{n=1}^{n=p} \lambda_n \varepsilon_n \\ &\Rightarrow \sum_{n=1}^{n=p} \lambda_n(f(x^n) - f(u)) \leq D_h(u, x^0) - D_h(u, x^p) + \sum_{n=1}^{n=p} \lambda_n \varepsilon_n \end{aligned}$$

Since  $\{f(x^n)\}$  is decreasing, we have :

$$(f(x^p) - f(u)) \sum_{n=1}^{n=p} \lambda_n \leq D_h(u, x^0) - D_h(u, x^p) + \sum_{n=1}^{n=p} \lambda_n \varepsilon_n \tag{9}$$

then,

$$f(x^p) - f(u) \leq \frac{1}{t_p} [D_h(u, x^0) + \sum_{n=1}^{\infty} \lambda_n \varepsilon_n]. \tag{10}$$

(b)

$$t_p = \lambda p \Rightarrow (7).$$

□

Now , we derive a global convergence of the sequence generated by (IEP) to a minimizer of (P) .

**Theorem 3.5.**

(a) If  $\sum \lambda_n = +\infty$  and  $\varepsilon_n \rightarrow 0$  then  $f(x^n) \rightarrow \inf_{\bar{S}}$

(b) If, moreover  $\arg \min_{\bar{S}} f \neq \emptyset$  and  $\sum \lambda_n \varepsilon_n < +\infty$  then  $x^n \rightarrow x^* \in \arg \min_{\bar{S}} f$

Proof. (a)

$$(10) \Rightarrow f(x^p) \leq f(u) + \frac{D_h(u, x^0)}{t_p} + \frac{\sum_{n=1}^{n=p} \lambda_n \varepsilon_n}{t_p}, \text{ when } t_p \rightarrow +\infty,$$

$$\overline{\lim} f(x^p) \leq \inf_{\bar{S}}. \tag{11}$$

As  $\underline{\lim} f(x^p) \geq \inf_{\bar{S}}$ , we deduce

$$\lim f(x^p) = \inf_{\bar{S}}.$$

(b) Let  $x^* \in \arg \min_{\bar{S}} f$ , we put  $u = x^*$  in (8), we have

$$D_h(x^*, x^n) \leq D_h(x^*, x^{n-1}) + \lambda_n \varepsilon_n \tag{12}$$

Since  $\sum \lambda_n \varepsilon_n < +\infty$ , we have

$$D_h(x^*, x^n) \rightarrow l \geq 0 \tag{13}$$

From  $H_3$ ,  $\{x^n\}_n$  is bounded . Let  $u^* \in \text{Adh}\{x^n\}$ , it exists then a sub-sequence  $\{x^{n_i}\}$  of  $\{x^n\}_n$  such as  $x^{n_i} \rightarrow u^*$  .  $u^* \in \arg \min_{\bar{S}} f$ . Indeed :

$$\inf_{\bar{S}} \leq f(u^*) \leq f(x^{n_i}) = \inf_{\bar{S}} \Rightarrow \inf_{\bar{S}} = f(u^*),$$

which shows that  $u^* \in \arg \min_{\bar{S}} f$ , therefore  $D_h(u^*, x^n) \rightarrow l'$ .

Since  $x^{n_i} \rightarrow u^* \in \bar{S}$  , from  $H_4$  , we are getting :

$$D_h(u^*, x^{n_i}) \rightarrow 0,$$



then  $l' = 0$ , i.e.,  $D_h(u^*, x^n) \rightarrow 0$ . The convergence of  $x^n$  to  $u^*$  results immediately from the following lemma :

**Lemma 3.6.** If  $\{x^n\} \subset S$  and  $D_h(u^*, x^n) \rightarrow 0$  then  $x^n \rightarrow u^*$ .

Proof : From  $H_3$ ,  $\{x^n\}$  is bounded. Let  $x^* \in Adh\{x^n\}$ , it exists then the sub-sequence  $\{x^{n_i}\}$  of  $\{x^n\}$  such that  $x^{n_i} \rightarrow x^*$ . From  $H_5$  :

$$D_h(u^*, x^{n_i}) \rightarrow 0 \text{ and } x^{n_i} \rightarrow x^* \in \bar{S} \Rightarrow x^* = u^*$$

$$\begin{aligned} &\Rightarrow Adh\{x^n\} = \{x^*\} \\ &\Rightarrow \qquad \qquad \qquad x^n \qquad \qquad \qquad \rightarrow \\ &\qquad \qquad \qquad u^* \qquad \qquad \qquad \qquad \qquad \qquad \square \end{aligned}$$

**Corollary 3.7.** we suppose that  $ri(dom f) \subset S$ .

(a) If  $\sum \lambda_n = +\infty$  and  $\varepsilon_n \rightarrow 0$  then  $f(x^n) \rightarrow inf f$ .

(b) If, moreover  $argmin f \neq \emptyset$  and  $\sum \lambda_n \varepsilon_n < +\infty$  then  $x^n \rightarrow x^* \in argmin f$ .

Proof. Is a simple consequence of Theorem 3.5. □

#### 4. ANALYSIS OF THE ENTROPIC BUNDLE ALGORITHMS

In what follows, we will deduce the results of convergence (Theorem 4.5. - 4.6.) for Entropic Bundle Algorithms . First, we need to establish some technical results.

Let  $h \in B(S)$ . Let  $f \in \Gamma_0(R^d)$  and  $F$  a convex function with a finite values . We suppose that  $f$  verifies :

$$(A_1) : \qquad \qquad \qquad f = F + \Psi_{\bar{S}}$$

Let  $\{\varphi^k\}_k$  a sequence of functions belonging to  $\Gamma_0(R^d)$  such as :

$$(A_2) : \qquad \qquad \forall x \in S, \forall \lambda > 0, y^k := prox_{\lambda \varphi^k}^h(x) , \text{ exists and belongs to } S.$$

(The conditions of realisation of  $(A_2)$  are given in the Remark 4.7.). From (2)

$$\Upsilon^k := \frac{\nabla h(x) - \nabla h(y^k)}{\lambda} \in \partial\varphi^k(y^k).$$

Let's put :

$$\ell^k(y) := \varphi^k(y^k) + \langle \Upsilon^k, y - y^k \rangle$$

$$\bar{\ell}^k(y) := \ell^k(y) + \lambda^{-1}D_h(y, x)$$

$$\bar{\varphi}^k(y) := \varphi^k(y) + \lambda^{-1}D_h(y, x).$$

Furthermore we suppose :

$$(A_3) : \quad \varphi^k \leq f, \quad \forall k = 1, \dots$$

$$(A_4) : \quad \ell^k \leq \varphi^{k+1}.$$

$$(A_5) : \quad f(y^k) + \langle g^k, y - y^k \rangle \leq \varphi^{k+1}(y) \quad \text{where : } g^k \in \partial F(y^k).$$

**Proposition 4.1.** Let  $h \in B(S)$ . Let  $\{x^k\} \subset S$  bounded and  $\{y^k\} \subset \bar{S}$  bounded, such as  $D_h(y^k, x^k) \rightarrow 0$ . Then  $\|y^k - x^k\| \rightarrow 0$ .

Proof. Since  $\{y^k\}$  and  $\{x^k\}$  are bounded , the sequence  $\{\|y^k - x^k\|\}_k$  is bounded too. Let's show that  $Adh\{\|y^k - x^k\|\} = \{0\}$  . Let  $\delta \in Adh\{\|y^k - x^k\|\}$  , it exists a sub-sequence  $\{\|y^{k_i} - x^{k_i}\|\}_{k_i}$  such as:

$$\|y^{k_i} - x^{k_i}\| \rightarrow \delta.$$

$\{x^{k_i}\}$  is bounded , it exists  $\{x^{k_j}\}$  such that  $x^{k_j} \rightarrow x^*$  . Otherwise

$$\{x^k\} \subset S \Rightarrow x^* \in \bar{S}.$$

From  $H_5$  ,

$$D_h(y^{k_j}, x^{k_j}) \rightarrow 0 \text{ and } x^{k_j} \rightarrow x^* \Rightarrow y^{k_j} \rightarrow x^*.$$

It follows that  $\|y^{k_j} - x^{k_j}\| \rightarrow 0$  , which means :  $\delta = 0$ . □

**Proposition 4.2.** If  $f$  verifies  $A_1$  and  $\{\varphi^k\}_{k \geq 1}$  verifies  $A_2, A_3, A_4$  and  $A_5$ , then :

- (i)  $0 \leq f(y^k) - \varphi^k(y^k) \rightarrow 0$ ,  
(ii)  $y^k \rightarrow \text{prox}_{\lambda f}^h x$ .

Proof . (i)

$$\begin{aligned} \bar{\ell}^k(y) - \bar{\ell}^k(y^k) &= \ell^k(y) + \lambda^{-1}D_h(y, x) - \ell^k(y^k) - \lambda^{-1}D_h(y^k, x) \\ &= \langle \Upsilon^k, y - y^k \rangle + \lambda^{-1}D_h(y, x) - \lambda^{-1}D_h(y^k, x) \\ &= \lambda^{-1} \langle \nabla h(x) - \nabla h(y^k), y - y^k \rangle + \lambda^{-1}D_h(y, x) - \\ &\quad \lambda^{-1}D_h(y^k, x). \end{aligned}$$

From the Lemme 2.2.,

$$\langle \nabla h(x) - \nabla h(y^k), y - y^k \rangle = D_h(y, y^k) + D_h(y^k, x) - D_h(y, x)$$

It follows that :

$$\bar{\ell}^k(y) = \bar{\ell}^k(y^k) + \lambda^{-1}D_h(y, y^k) \quad (14)$$

For  $x \in S$ ,

$$\begin{aligned} f(x) &\geq \varphi^{k+1}(x) = \bar{\varphi}^{k+1}(x) \\ &\geq \bar{\varphi}^{k+1}(y^{k+1}) = \bar{\ell}^{k+1}(y^{k+1}) \\ &\geq \bar{\ell}^k(y^{k+1}) = \bar{\ell}^k(y^k) + \lambda^{-1}D_h(y^{k+1}, y^k). \end{aligned} \quad (15)$$

We deduce that

$$f(x) \geq \bar{\ell}^k(y^k) \quad (16)$$

$$\bar{\ell}^{k+1}(y^{k+1}) \geq \bar{\ell}^k(y^k) + \lambda^{-1}D_h(y^{k+1}, y^k) \quad (17)$$

Since  $x \in \text{dom}f$ , from (16) and (17), we can deduce that

$$\bar{\ell}^k(y^k) \rightarrow \ell \in R. \quad (18)$$

On the other hand

$$(17) \Rightarrow D_h(y^{k+1}, y^k) \rightarrow 0.$$

For  $y$  fixed in (14) , and due to (18), we deduce that the sequence  $\{D_h(y, y^k)\}_k$  is bounded. From  $H_3$ ,  $\{y^k\}$  is bounded . By vertue of the Proposition 4.1. ,

$$\|y^{k+1} - y^k\| \rightarrow 0. \tag{19}$$

From the other hand ,

$$f(y^{k+1}) - f(y^k) \geq \varphi^{k+1}(y^{k+1}) - f(y^k) \geq \langle g^k, y^{k+1} - y^k \rangle,$$

and from  $(A_1)$  and  $(A_2)$  ,

$$F(y^{k+1}) - F(y^k) \geq \varphi^{k+1}(y^{k+1}) - f(y^k) \geq \langle g^k, y^{k+1} - y^k \rangle,$$

$F$  is at finite values , so locally Lipschitz , which leads , with (19),

$$F(y^{k+1}) - F(y^k) \rightarrow 0.$$

Since  $g^k \in \partial F(y^k)$  and  $\{y^k\}$  is bounded,  $\{g^k\}$  is bounded, then

$$\varphi^{k+1}(y^{k+1}) - f(y^k) \rightarrow 0.$$

Otherwise ,

$$0 \leq f(y^k) - \varphi^k(y^k) = F(y^k) - F(y^{k-1}) + F(y^{k-1}) - \varphi^k(y^k).$$

It follows that

$$f(y^k) - \varphi^k(y^k) \rightarrow 0.$$

ii. the sequence  $\{y^k\}_k$  verifies  $\frac{\nabla h(x) - \nabla h(y^k)}{\lambda} \in \partial_{\varepsilon_k} f(y^k)$  where  $\varepsilon_k = f(y^k) - \varphi^k(y^k)$ , thus the convergence of  $y^k$  towards  $prox_{\lambda f}^h$  results immediatly from the following Lemme:

**Lemma 4.3.** Let  $\{y^k\}_k \subset S$  such as:

- i-  $\frac{\nabla h(x) - \nabla h(y^k)}{\lambda} \in \partial_{\varepsilon_k} f(y^k)$ ,
- ii-  $\varepsilon_k \rightarrow 0$ .

Then :

- (a)  $D_h(y^k, \text{prox}_{\lambda f}^h x) + D_h(\text{prox}_{\lambda f}^h x, y^k) \leq \lambda \varepsilon_k$ ,  
 (b)  $y^k \rightarrow \text{prox}_{\lambda f}^h x$ .

**Proof.** (a)  $\frac{\nabla h(x) - \nabla h(y^k)}{\lambda} \in \partial_{\varepsilon_k} f(y^k)$  and  $\frac{\nabla h(x) - \nabla h(\text{prox}_{\lambda f}^h x)}{\lambda} \in \partial_{\varepsilon_k} f(\text{prox}_{\lambda f}^h x)$ , it follows that

$$\langle \nabla h(y^k) - \nabla h(\text{prox}_{\lambda f}^h x), y^k - \text{prox}_{\lambda f}^h x \rangle \leq \lambda \varepsilon_k,$$

Let again ,

$$D_h(y^k, \text{prox}_{\lambda f}^h x) + D_h(\text{prox}_{\lambda f}^h x, y^k) \leq \lambda \varepsilon_k,$$

- (b)  $D_h(y^k, \text{prox}_{\lambda f}^h x) \rightarrow 0$  , so from  $H_5$ ,  $y^k \rightarrow \text{prox}_{\lambda f}^h x$ . □

**Example 4.4.** If  $h$  verifies the conditions of the proposition 2.6., Then  $(A_2)$  is verified, we give below two exemples of sequences  $\{\varphi^k\}$  verifying  $(A_3)$ ,  $(A_4)$  and  $(A_5)$  :

$$E_1 : \varphi^{k+1}(y) = \max\{f(y^i) + \langle g^i, y - y^i \rangle, 1 \leq i \leq k\}$$

$$E_2 : \varphi^{k+1}(y) = \max\{\ell^k(y), f(y^k) + \langle g^k, y - y^k \rangle\}.$$

Now we represent below the Entropic Bundle Algorithms obtained by replacing the quadratic kernel in the base method with entropic distances.

#### Algorithm 2 : Entropic Bundle Algorithm (EBA)

- 1: input:  $m \in ]0, 1[$ ,  $x_1 \in S$  and  $k(1) := 0$   
 2: for  $n = 1, 2, \dots$  with  $\lambda_n > 0$  and  $\varepsilon_n \geq 0$  , do  
 3: for  $k = k(n) + 1, \dots, k(n + 1)$ , compute

$$y^k := \text{prox}_{\lambda_n \varphi^k}^h x_n ,$$

where  $k(n + 1)$  is the first natural integer  $k > k(n)$  for which an improvement is obtained , precisely :

$$(*) : f(x_n) - f(y^k) \geq m [f(x_n) - \varphi^k(y^k)] .$$

- 4: (i) If the condition (\*) is never verified , we put  $k(n + 1) := +\infty$  and stop  
(ii) If not , we put  $x_{n+1} = y^{k(n+1)}$  go to step 3.
- 

**Theorem 4.5.** Let  $\{x_n\}$  the generated sequence by the Entropic Bundle Algorithms .  
From two things the one :

- (a) It exists n such as  $k(n + 1) = +\infty$  then  $x_n$  minimizes f.
- (b) The sequence k(n) is infinite , then if  $\sum_n \lambda_n = +\infty$ ,  $f(x_n) \rightarrow \text{inf} f$ . If furthermore ,  $0 < \lambda_k \leq \bar{\lambda} < +\infty$  and  $\text{argmin} f \neq \emptyset$  , then

$$x_n \rightarrow \bar{x} \in \text{argmin} f.$$

Proof . (a) (\*) is not verified , it exists then a rank n such as :

$$f(x_n) - f(y^k) < m [f(x_n) - \varphi^k(y^k)] , \quad \forall k \geq k(n) + 1.$$

Which leads :

$$(1 - m) [f(x_n) - f(y^k)] < m [f(y^k) - \varphi^k(y^k)] .$$

According to the Proposion 4.2.,  $f(y^k) - \varphi^k(y^k) \rightarrow 0$ , then  $f(x_n) \leq f(\text{prox}_{\lambda_n f}^h x_n)$ .  
Otherwise  $f(\text{prox}_{\lambda_n f}^h x_n) + \lambda_n^{-1} D_h(\text{prox}_{\lambda_n f}^h x_n, x_n) \leq f(x_n)$ , then

$$f(\text{prox}_{\lambda_n f}^h x_n) + \lambda_n^{-1} D_h(\text{prox}_{\lambda_n f}^h x_n, x_n) \leq f(\text{prox}_{\lambda_n f}^h x_n)$$

Since  $\text{prox}_{\lambda_n f}^h x_n \in \bar{S} = \text{dom} f$ , we have  $D_h(\text{prox}_{\lambda_n f}^h x_n, x_n) = 0$ , i.e.  $\text{prox}_{\lambda_n f}^h x_n = x_n \in S$ . From (2),  $0 \in \partial f(x_n)$ , then  $x_n \in \text{Argmin} f$ .

- (b)  $\frac{\nabla h(x_n) - \nabla h(x_{n+1})}{\lambda_n} \in \partial \varphi^{k(n+1)}(x_{n+1}) \Rightarrow \frac{\nabla h(x_n) - \nabla h(x_{n+1})}{\lambda_n} \in \partial_{\varepsilon_{n+1}} f(x_{n+1})$ , where  $\varepsilon_{n+1} = f(x_{n+1}) - \varphi^{k(n+1)}(x_{n+1})$ .

From (\*), we have

$$0 \leq \varepsilon_{n+1} \leq \frac{1 - m}{m} [f(x_n) - f(x_{n+1})],$$

therefore,  $f(x_n)$  is decreasing and  $\sum_n \lambda_n \varepsilon_n < +\infty$ . as  $\text{ri}(\text{dom}f) = S$ , therefore by application of the Corollary 3.7. , we deduce the result .  $\square$

In order to avoid the calculation of  $y^k$  indefinitely, and since  $f(y^k) - \varphi^k(y^k) \rightarrow 0$ , we propose the following algorithm :

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Algorithm 3: A version of the Entropic Bundle Algorithm (EBA)

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- 1: input:  $x_1 \in S$  and  $k(1) := 0$
- 2: for  $n = 1, 2, \dots$  with  $\lambda_n > 0$  and  $\alpha_n \geq 0$  , do
- 3: for  $k = k(n) + 1, \dots, k(n+1)$ , compute

$$y^k := \text{prox}_{\lambda_n \varphi^k}^h x_n ,$$

where  $k(n+1)$  is the first natural integer  $k > k(n)$  such that :

$$(**) \quad f(y^k) - \varphi^k(y^k) \leq \alpha_{n+1}$$

- 4: put :  $x_{n+1} = y^{k(n+1)}$  go to step 3.
- 

As before, we have  $\frac{\nabla h(x_n) - \nabla h(x_{n+1})}{\lambda_n} \in \partial_{\varepsilon_{n+1}} f(x_{n+1})$  , where

$$\varepsilon_{n+1} = f(x_{n+1}) - \varphi^{k(n+1)}(x_{n+1}).$$

Since  $\varepsilon_{n+1} \leq \alpha_{n+1}$  , the convergence result of this algorithm is given by :

**Theorem 4.6.** Let  $\{x_n\}$  the generated sequence by Algorithm 3

- (i) If  $\sum_n \lambda_n = +\infty$  and  $\alpha_k \rightarrow 0$  then  $\liminf f(x_n) = \text{inf} f$ .
- (ii) If, moreover ,  $0 < \lambda_k \leq \bar{\lambda} < +\infty$  ,  $\sum_k \alpha_k < +\infty$  and  $\text{Argmin} f \neq \emptyset$  then

$$\lim f(x_n) = \text{inf} f \text{ and } x_n \rightarrow \bar{x} \in \text{argmin} f.$$

Proof. Immediate consequence of Corollary 3.7.  $\square$

**Remark 4.7.**

(i) If  $Im \nabla h = R^d$  and  $ri(dom \varphi^k) \cap S \neq \emptyset$ , then according to the Proposition 2.6.  $(A_2)$  is always verified

(ii) If  $S = R^d$ , then  $(A_2)$  is checked and the Algorithms (2) and (3) solve (P) where  $f$  is finite values

**5. CONCLUSION**

The proposed class of methods (EBA) contains the bundle method (BM) described by Correa-Lemaréchal [13] and solves convex optimization problems under positive constraints:

(i) If  $h = h_0$  then  $(EBA) \Leftrightarrow (BM)$

(ii) For  $F: R^d \rightarrow R$  convex, let the problem of convex optimization:

$$(P') : \min\{F(x), x \in \Omega\} \text{ where } \Omega \text{ is the positive cone of } R^d$$

For  $h \in B(S)$ , with  $S = int(\Omega)$ , (for example  $h = h_1$ ), (EBA) solves  $(P')$  without using the dual problem, like Teboulle [17] and Eckstein [4].

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