

Strongly quasiconvex functions: what we know (so far)

Sorin-Mihai Grad

based on joint work with Felipe Lara, Raúl Marcavillaca, Huu Nhan Nguyen

Optimization Theory: Concepts, Methods, and Applications



► $h : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$ with a convex domain¹ is

- **strongly convex**: $\exists \gamma \in]0, +\infty[$ s.t. $\forall x, y \in \text{dom } h \ \forall \lambda \in [0, 1]$

$$h(\lambda y + (1 - \lambda)x) \leq \lambda h(y) + (1 - \lambda)h(x) - \lambda(1 - \lambda)\frac{\gamma}{2}\|x - y\|^2$$

- **strongly quasiconvex**²: $\exists \gamma \in]0, +\infty[$ s.t. $\forall x, y \in \text{dom } h$
 $\forall \lambda \in [0, 1]$

$$h(\lambda y + (1 - \lambda)x) \leq \max\{h(y), h(x)\} - \lambda(1 - \lambda)\frac{\gamma}{2}\|x - y\|^2$$

► both properties can be considered on a set $U \subseteq \text{dom } h$, too

► strongly convex $\Rightarrow$ strongly quasiconvex

► $\|\cdot\|$ is strongly quasiconvex on any bounded convex $U \subseteq \mathbb{R}^n$
 but *not* strongly convex

► $\sqrt{\|\cdot\|}$ is strongly quasiconvex on any bounded convex $U \subseteq \mathbb{R}^n$
 but *not* convex

► any constant function is convex but *not* strongly quasiconvex

¹ $\text{dom } h = \{x \in \mathbb{R}^n : h(x) < +\infty\}$

²introduced by Polyak, 1966

- ▶ the composition of a strongly quasiconvex function with a linear operator is strongly quasiconvex
- ▶ the maximum of finitely many strongly quasiconvex functions is strongly quasiconvex
- ▶ a strongly quasiconvex function cannot be bounded from above on an unbounded set³
- ▶ $K \subseteq \mathbb{R}^n$ solid convex cone, $h : K \rightarrow \mathbb{R}$ quadratic: h strongly quasiconvex $\Leftrightarrow h$ strongly convex⁴
- ▶ $\emptyset \neq K \subseteq \mathbb{R}^n$ convex, $h : K \rightarrow \mathbb{R}$: h strongly quasiconvex $\Leftrightarrow$

$$t \in \mathbb{R} \mapsto h \left(x + \frac{t}{\|x - y\|} (x - y) \right)$$

strongly quasiconvex on $[0, \|x - y\|] \forall x \neq y \in K$ ⁵

³Jovanović, 1996

⁴Jovanović, 1993

⁵Jovanović, 1996

- ▶ a strongly quasiconvex function is 2-supercoercive⁶
- ▶ a proper strongly quasiconvex function has at most one minimizer on a convex set that touches its domain
- ▶ a proper lsc strongly quasiconvex function has *one* minimizer on a closed convex set⁷
- ▶ $\emptyset \neq K \subseteq \mathbb{R}^n$ closed convex, $h : K \rightarrow \mathbb{R}$ lsc strongly quasiconvex, $\beta > 0 \Rightarrow \text{Prox}_{\beta h + \delta_K}(\cdot) \neq \emptyset$ ⁸ (but not necessarily singleton)
- ▶ $K \subseteq \mathbb{R}^n$ closed convex, $h : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$ proper lsc strongly quasiconvex, $K \subseteq \text{dom } h$, $\beta > 0 \Rightarrow$

$$\text{Fix}(\text{Prox}_{\beta h + \delta_K}) = \arg \min_K h^9$$

⁶ $h : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$, $\liminf_{\|x\| \rightarrow +\infty} \frac{h(x)}{\|x\|^2} > 0$

⁷Lara, 2022

⁸Lara, 2022

⁹Korablev, 1980; Kabgani & Lara, 2022

- $\emptyset \neq K \subseteq \mathbb{R}^n$ convex, $h : K \rightarrow \mathbb{R}$ strongly quasiconvex,
 $\arg \min_K h = \{\bar{x}\} \Rightarrow$

$$h(x) - h(\bar{x}) \geq \frac{\gamma}{8} \|x - \bar{x}\|^2 \quad \forall x \in K$$

- $h : \mathbb{R}^n \rightarrow \mathbb{R}$ proper with $\text{dom } h$ convex - t.f.a.e.¹⁰
- (a) h convex
 - (b) $h + \frac{1}{2\beta} \|z - \cdot\|^2$ strongly convex $\forall z \in \mathbb{R}^n \quad \forall \beta > 0$
 - (c) $h + \frac{1}{2\beta} \|z - \cdot\|^2$ quasiconvex $\forall z \in \mathbb{R}^n \quad \forall \beta > 0$
 - (d) $h + \frac{1}{2\beta} \|z - \cdot\|^2$ strongly quasiconvex $\forall z \in \mathbb{R}^n \quad \forall \beta > 0$
- some properties also hold in Hilbert spaces

¹⁰Lara, 2022

- ▶ $\emptyset \neq K \subseteq \mathbb{R}^n$, $h : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$ proper, $\beta > 0$
- ▶ the (β, γ, K) -strong subdifferential of h at $\bar{x} \in K \cap \text{dom } h$ is¹¹

$$\begin{aligned} \partial_{\beta, \gamma}^K h(\bar{x}) = & \left\{ z \in \mathbb{R}^n : \max\{h(y), h(\bar{x})\} \geq h(\bar{x}) + \frac{t}{\beta} z^\top (y - \bar{x}) \right. \\ & \left. + \frac{t}{2} \left(\gamma - \frac{t}{\beta} - t\gamma \right) \|y - \bar{x}\|^2 \quad \forall y \in K \quad \forall t \in [0, 1] \right\} \end{aligned}$$

- ▶ when $K = S_{h(\bar{x})}(h)$, $\partial_{\beta, \gamma} h(\bar{x}) := \partial_{\beta, \gamma}^{S_{h(\bar{x})}(h)} h(\bar{x})$ is the (β, γ) -strong sublevel subdifferential of h at $\bar{x}$
- ▶ K closed convex & h strongly quasiconvex $\Rightarrow \partial_{\beta, \gamma}^K h(x) \neq \emptyset$
closed convex $\forall x \in K$

¹¹Kabgani & Lara, 2022

- $\emptyset \neq K \subseteq \mathbb{R}^n$ convex, $h: K \rightarrow \mathbb{R}$ C^1 : h strongly quasiconvex $\Leftrightarrow$

$$h(x) \leq h(y) \implies \nabla h(y)^\top (y - x) \geq \frac{\gamma}{2} \|x - y\|^2, \forall x, y \in K^{12}$$

- $\emptyset \neq K \subseteq \mathbb{R}^n$ convex, $h: K \rightarrow \mathbb{R}$ C^1 : h strongly quasiconvex
 $\Leftrightarrow \nabla h(x) \in \partial_{1,\gamma} h(x) \forall x \in K \cap \text{dom } h^{13}$

- $\emptyset \neq K \subseteq \mathbb{R}^n$ convex, $h: K \rightarrow \mathbb{R}$ C^1 & strongly quasiconvex,
 ∇h L -Lipschitz-continuous, $\arg \min_K h = \{\bar{x}\} \Rightarrow$

$$\|\nabla h(x)\|^2 \geq \frac{2\gamma^2}{L} (h(x) - h(\bar{x})), \forall x \in K^{14}$$

¹²Vladimirov & Nesterov & Chekanov, 1978

¹³Lara & Marcavillaca & Vuong, 2024

¹⁴Polyak-Łojasiewicz-Kurdyka property, Korablev, 1980

- ▶ $t \in \mathbb{R} \mapsto |t + a|$ ($a \in \mathbb{R}$) is convex, and strongly quasiconvex with modulus $\gamma > 0$ on $[0, 1/\gamma]$ but not strongly convex
- ▶ $t \in \mathbb{R} \mapsto -t^2 - t$ is strongly quasiconvex on $[0, 1]$
- ▶ $\forall c \in \mathbb{R} \ \& \ d > 0 \ \exists \delta > 0: t \in \mathcal{B}(0, \delta) \mapsto c - de^{-x^2}$ is strongly quasiconvex on $\mathcal{B}(0, \delta)$
- ▶ $t \in \mathbb{R} \mapsto t^2 + 3 \sin^2 t$ is strongly quasiconvex
- ▶ $f : [0, 1] \rightarrow \mathbb{R}, f(t) = \begin{cases} 0, & t = 0 \\ -\frac{1}{t}, & t \in]0, 1] \end{cases}$ is strongly quasiconvex on $[0, 1]$
- ▶ $t \mapsto \sqrt[4]{t^2 + k^2}$ ($k \in \mathbb{R}$) is strongly quasiconvex on any interval $[-c, c] \subseteq \mathbb{R}$
- ▶ $\|\cdot\|^\alpha$ ($0 < \alpha < 1$) is strongly quasiconvex on nonempty bounded convex sets in $\mathbb{R}^n$

- $\emptyset \neq K \subseteq \mathbb{R}^n$, $h : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$, $g : \mathbb{R}^n \rightarrow \mathbb{R}$: $K \cap \text{dom } h \neq \emptyset$, $g(K) \subseteq]0, M[$, h is strongly convex $\Rightarrow h/g$ is strongly quasiconvex on K when one of the following holds

- (a) g is affine
- (b) h is nonnegative on $\text{dom } h$ and g is concave
- (c) h is nonpositive on $\text{dom } h$ and g is convex

- $A, B \in \mathbb{R}^{n \times n}$, $A \in \mathcal{S}_{++}^n$, $a, b \in \mathbb{R}^n$, $\alpha, \beta \in \mathbb{R}$,
 $K = \{x \in \mathbb{R}^n : m \leq (1/2)x^\top Bx + b^\top x + \beta \leq M\}$
 $(0 < m < M) \Rightarrow$

$$x \in K \mapsto \frac{\frac{1}{2}x^\top Ax + a^\top x + \alpha}{\frac{1}{2}x^\top Bx + b^\top x + \beta} \in \mathbb{R}$$

is strongly quasiconvex on K if any of the following holds

- (a) $B = 0 \in \mathbb{R}^{n \times n}$
- (b) $(1/2)x^\top Ax + a^\top x + \alpha \geq 0$ for all $x \in K$ and $B \in -\mathcal{S}_+^n$
- (c) $(1/2)x^\top Ax + a^\top x + \alpha \leq 0$ for all $x \in K$ and $B \in \mathcal{S}_+^n$

- ▶ $K \subseteq \mathbb{R}^n$ affine subspace
- ▶ $h : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$ proper lsc, strongly quasiconvex on K
- ▶ $K \subseteq \text{dom } h$

$$\min_{x \in K} h(x) \quad (\text{COP})$$

Step 0. let $x^0 = x^{-1} \in K$, $\alpha \in [0, 1[$, $0 < \rho' \leq \rho'' < 2$,
 $\{c_k\}_{k \in \mathbb{N}} \subseteq \mathbb{R}_{++}$, $k = 0$

Step 1. choose $\alpha_k \in [0, \alpha]$, set

$$y^k = x^k + \alpha_k(x^k - x^{k-1}) \quad [\textit{inertial step}]$$

and compute¹⁵

$$z^k \in \text{Prox}_{c_k(h+\delta_K)}(y^k) \quad [\textit{proximal step}]$$

Step 2. if $z^k = y^k$: STOP $\Rightarrow y^k \in \arg \min_K h$

Step 3. choose $\rho_k \in [\rho', \rho'']$ and update

$$x^{k+1} = (1 - \rho_k)y^k + \rho_k z^k \quad [\textit{relaxation step}]$$

Step 4. $k = k + 1$ and go to Step 1

¹⁵indicator fct of K : $\delta_K : \mathbb{R}^n \rightarrow \overline{\mathbb{R}}$, $\delta(x) = 0$, $x \in K$; $\delta(x) = +\infty$, $x \notin K$

- ▶ if $\alpha = 0$ & $\rho_k = 1$, $k \geq 0$ the algorithm collapses to PPA¹⁶
- ▶ K can be taken **closed convex**
 - when $0 < \rho' \leq \rho'' < 1$ with the alternate relaxation step

$$x^{k+1} = (1 - \rho_k)x^k + \rho_k z^k$$

- ▶ by adding a projection on K in the relaxation step

$$x^{k+1} = \text{Pr}_K((1 - \rho_k)y^k + \rho_k z^k)$$

- ▶ by removing the inertial steps ($\alpha = 0$) and taking $0 < \rho' \leq \rho'' < 1$

- ▶ Bregman PPA¹⁷

¹⁶Lara, 2022

¹⁷Lara & Marcavillaca, 2024

- ▶ $0 < \rho' \leq \rho'' < 2$, $\{\rho_k\}_k \subseteq [\rho', \rho'']$, $\alpha \in [0, 1[$, $\{\alpha_k\}_k \subseteq [0, \alpha]$
- ▶ $\{\alpha_k\}_k$ is nondecreasing satisfying

$$0 \leq \alpha_k \leq \alpha_{k+1} \leq \alpha < \frac{1}{3} \quad \forall k \geq 0$$

- ▶ $\Omega := \{x \in K : h(x) \leq h(z^k) \quad \forall k \in \mathbb{N}\}$

$\Rightarrow$

- $\forall x^* \in \Omega \exists \lim_{k \rightarrow \infty} \|x^k - x^*\|$ and

$$\lim_{k \rightarrow +\infty} \|x^{k+1} - y^k\| = \lim_{k \rightarrow +\infty} \|z^k - y^k\| = 0$$

- if, in addition, $c_k \geq c' > 0 \quad \forall k \geq 0$

$$\Rightarrow \begin{cases} x^k \rightarrow \bar{x} = \arg \min_K h \\ \lim_{k \rightarrow +\infty} h(x^k) = \min_K h \end{cases}$$

- $\alpha = 0, \rho_k \in (0, 1), r_k = \sqrt{1 - \frac{\rho_k c_k \gamma}{1 + c_k \gamma}} \in (0, 1), k \geq 0 \Rightarrow$
- $\|x^{k+1} - \bar{x}\| \leq r_k \|x^k - \bar{x}\| \quad \forall k \geq 0$
 - $\|z^k - x^k\|^2 \leq \frac{r_k}{\rho_k(1-\rho_k)} \|x^k - \bar{x}\|^2 \quad \forall k \geq 0$
 - $f(z^k) - \min_K f \leq \frac{r_{k-1}}{2c_k} \|x^{k-1} - \bar{x}\|^2 \quad \forall k \geq 0$

Step 0. let $\beta, \gamma > 0$, $\{\alpha_j\}_j \subseteq]0, \frac{1}{\gamma\beta}[$, $x^0 \in K$, $k = 0$

Step 1. if $0_n \in \partial_{\beta, \gamma}^K h(x^k)$: STOP

Step 2. determine

$$\xi^k \in \partial_{\beta, \gamma}^K h(x^k) \quad [\textit{subgradient step}]$$

Step 3. $x^{k+1} := \text{Pr}_K(x^k - \alpha_k \xi^k)$ [projection step]

Step 4. $k = k + 1$ and go to Step 1

- ▶ K closed convex, $K \subseteq \text{int dom } h$
- ▶ $\beta > 0, M > 0: \|\xi\| \leq M \ \forall \xi \in \partial_{\beta, \gamma}^K h(x) \ \forall x \in K$
- ▶ $\{\alpha_j\}_j \subseteq]0, 1/(\gamma\beta)[: \sum_{k=0}^{+\infty} \alpha_k = +\infty \ \& \ \sum_{k=0}^{+\infty} \alpha_k^2 < +\infty$
 $\Rightarrow$
 - $x^k \rightarrow \bar{x} = \arg \min_K h$
 - $\lim_{k \rightarrow +\infty} h(x^k) = \min_K h$
 - $+ h$ continuous $\Rightarrow \lim_{k \rightarrow +\infty} h(x^k) = h(\bar{x}) = \min_K h$

- ▶ $h \in C^1$
- ▶ $K = \mathbb{R}^n$

Step 0. let $\alpha > 0$, $\{\alpha_j\}_j \subseteq [\alpha, +\infty[$, $\{\psi^j\}_j \in \ell^1$, $x^0 \in \mathbb{R}^n$ and $k = 0$

Step 1. if $\nabla h(x^k) = 0_n$: STOP

Step 2. determine

$$x^{k+1} = x^k + \alpha_k \nabla h(x^k) + \psi^k \quad [\textit{gradient step}]$$

Step 3. $k = k + 1$ and go to Step 1

- ▶ ∇h Lipschitz-continuous & $\{x^k\}_k$ bounded $\Rightarrow$
 $x^k \rightarrow \bar{x} = \arg \min_K h$ ¹⁸
- ▶ $\psi^k = 0 \ \forall k \geq 0$, ∇h locally Lipschitz-continuous, $\exists \alpha, \bar{\alpha} > 0$:
 $\alpha \leq \alpha_k \leq \bar{\alpha} < \min\{\gamma/\bar{L}^2, 2/\bar{L}\} \Rightarrow x^k \rightarrow \bar{x} = \arg \min_K h$ ¹⁹

¹⁸Rouhani & Rahimi Piranfar, 2021

¹⁹Lara & Marcavillaca & Vuong, 2024

- ▶ $h \in C^1$
- ▶ $K = \mathbb{R}^n$

Step 0. let $\alpha, \eta > 0$, $\theta = 1 - \alpha\eta$, $x^0, x^1 \in \mathbb{R}^n$, $k = 1$

Step 1. if $\nabla h(x^k) = 0_n$: STOP

Step 2. determine

$$x^{k+1} = x^k + \theta(x^k - x^{k-1}) - \eta^2 \nabla h(x^k) \quad [\textit{inertial step}]$$

Step 3. $k = k + 1$ and go to Step 1

- ▶ ∇h Lipschitz-continuous on bounded sets & $\{x^k\}_k$ bounded

$$\Rightarrow \begin{cases} x^k \rightarrow \bar{x} = \arg \min_K h \\ \lim_{k \rightarrow +\infty} h(x^k) = \min_K h \end{cases}$$

- ▶ $h \in C^1$
- ▶ $K = \mathbb{R}^n$

Step 0. let $\eta > 0$, $\{\alpha_j\}_j \subseteq [\eta, +\infty[$, $x^0, x^1 \in \mathbb{R}^n$, $k = 1$

Step 1. if $\nabla h(x^k) = 0_n$: STOP

Step 2. determine

$$x^{k+1} = 2x^k - x^{k-1} + \alpha_k \nabla h(x^k) \quad [\textit{inertial step}]$$

Step 3. $k = k + 1$ and go to Step 1

- ▶ ∇h Lipschitz-continuous & $\theta \in]0, 1[$

$$\Rightarrow \begin{cases} x^k \rightarrow \bar{x} = \arg \min_K h \\ \lim_{k \rightarrow +\infty} h(x^k) = \min_K h \end{cases}$$

- ▶ first-order [Rouhani & Rahimi Piranfar, 2021], [Lara & Marcavillaca & Vuong, 2024]
- ▶ second-order [Rahimi Piranfar & Khatibzadeh, 2021], [Lara & Marcavillaca & Vuong, 2024]

$$\text{find } \bar{x} \in K : f(\bar{x}, y) \geq 0, \forall y \in K$$

- ▶ solution set: $S(K, f)$
- ▶ $K \subseteq \mathbb{R}^n$ linear subspace
- ▶ $f : K \times K \rightarrow \mathbb{R}$
- ▶ $f(x, \cdot)$ strongly quasiconvex $\forall x \in K$
- ▶ $f(\cdot, y)$ usc $\forall y \in K$
- ▶ f (jointly) lsc and pseudomonotone on K , i.e.

$$f(x, y) \geq 0 \implies f(y, x) \leq 0 \quad \forall x, y \in K$$

- ▶ f satisfies the Lipschitz type condition $\exists \eta > 0$ s.t.
 $f(x, z) - f(x, y) - f(y, z) \leq \eta (\|x - y\|^2 + \|y - z\|^2) \quad \forall x, y, z \in K$
- ▶ $(f(x, x) = 0 \quad \forall x \in K)$

- ▶ the hypotheses guarantee that $S(K, f)$ is a singleton²⁰

²⁰[Iusem & Lara, JOTA, 2022]

- ▶ proximal point algorithm [Iusem & Lara, 2022]
- ▶ regularized algorithm [Iusem & Lara, 2022]
- ▶ extragradient algorithm [Muu & Yen, 2023]
- ▶ relaxed-inertial proximal point algorithm [G & Lara & Marcavillaca, 2024]
- ▶ proximal point algorithm with extrapolation terms [Izuchukwu & Ogwo & Shehu, 2024]
- ▶ two-step proximal point algorithm [Iusem & Lara & Marcavillaca & Yen, 2024]
- ▶ extragradient projection algorithm [Lara & Marcavillaca & Yen, 2024]

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