Convex Optimization for Computer Vision

Lecture: M. Möller Exercises: J. Geiping Summer Semester 2019 Universität Siegen Department ETI Computer Vision

## Weekly Exercises 4

Room: H-A-7116 Thursday, 30.05.2019, 8:30-10:00, Submission deadline: Wednesday, 29.05.2019, 18:00

## Theory: Subdifferentials, Lipschitz continuity, and fixed point iterations

**Exercise 1** (4 Points). We call a function  $E: \mathbb{R}^n \to \mathbb{R}$  absolutely one-homogeneous if

$$E(\alpha u) = |\alpha|E(u)$$

holds for all  $u \in \mathbb{R}^n$  and  $\alpha \in \mathbb{R}$ . Prove that

$$\partial E(u) = \{ p \in \mathbb{R}^n \mid \langle p, u \rangle = E(u), \quad E(v) \ge \langle p, v \rangle \ \forall v \in \mathbb{R}^n \}.$$

Exercise 2 (4 Points). Find examples for the following functions and explain why your example is correct:

- A continuously differentiable convex function that is not L-smooth.
- A Lipschitz continuous function that is not a contraction.
- $\bullet\,$  A function that is not differentiable, but Lipschitz continuous.
- A convex L-smooth function E and a step size  $\tau$  for which G defined by  $G(u) = u \tau \nabla E$  is not a non-expansive function.

**Exercise 3** (4 Points). Show that for any  $a, b \in \mathbb{R}^n$ ,  $\theta \in \mathbb{R}$  it holds that

$$||(1-\theta)a + \theta b||^2 = (1-\theta)||a||^2 + \theta||b||^2 - \theta(1-\theta)||a-b||^2$$

## Programming: Unstable step sizes

Exercise 4 (4 Points). Consider minimizing the energy

$$E(u) = \frac{1}{2} ||u - f||^2 + \alpha ||Du||_1.$$

It is easy to see that

$$p(u) := u - f + \alpha D^T \operatorname{sign}_0(Du) \in \partial E(u),$$

for  $sign_0(0) = 0$ .

Implement a gradient descent iteration of the form

$$u^{k+1} = u^k - \tau p(u^k),$$

vary the step size  $\tau$ , and measure how close your iterates are to being optimal by plotting  $||p(u^k)||_2$ . What do you observe? Depending on the step size, there should be (at least) two different types of behaviors.