# The non-monotonocity effect of accelerated optimization methods

## Marina Danilova Boris Polyak

Moscow Institute of Physics and Technology, Department of Control and Applied Mathematics

Institute of Control Sciences RAS, Laboratory of Adaptive and Robust Systems

June 28, 2018

#### Introduction

## Accelerated first-order algorithms

- Conjugate gradient
- Heavy-ball
- Nesterov's accelerated gradient

#### Mathematical Challenges

- Accelerated methods converge non-monotonically.
- Asymptotic estimates obtained for them can give a distorted representation of the method behavior.
- How to implement the algorithm for real problems correctly?

#### Contents

- Introduction
- Stating the problem
- 3 Analysis of non-monotonic behavior
- 4 Construction of the Lyapunov function
- 6 Practical part
- 6 Future research

# Stating the problem

#### Optimization problem

$$\min_{x \in R^n} f(x)$$

- $\bullet \ x \in R^n, \ f(x) : R^n \to R, \ f(x) \in \mathscr{F}_{L,\mu}^{1,1}$
- $\|\nabla f(x) \nabla f(y)\| \le L\|x y\|$ L > 0 - Lipschitz constant
- $f(y) \ge f(x) + \langle \nabla f(x), y x \rangle + \frac{1}{2}\mu ||x y||^2$  $\mu > 0$  - constant of strong convexity
- $\varkappa = \frac{L}{\mu}$  condition number
- quadratic case  $f(x) = \frac{1}{2} \langle Ax, x \rangle + \langle b, x \rangle, \ \mu I \leq A \leq LI$



# Stating the problem

## Heavy ball method (Polyak 1964)

$$x_{k+1} = x_k - \alpha \nabla f(x_k) + \beta (x_k - x_{k-1})$$

 $\alpha, \beta$  - method parameters

#### Known results

- local convergence:  $\alpha \in \left(0, \frac{2(1+\beta)}{L}\right), \ \beta \in [0,1)$
- optimal parameters:  $\alpha^* = \frac{1}{(\sqrt{L} + \sqrt{\mu})^2}, \ \beta^* = \left(\frac{\sqrt{L} \sqrt{\mu}}{\sqrt{L} + \sqrt{\mu}}\right)^2$
- best convergence rate:  $q^* = \sqrt{\beta^*}$
- asymptotic estimate:  $||x_k x^*|| = O(q^k)$



# Non-monotonicity effect

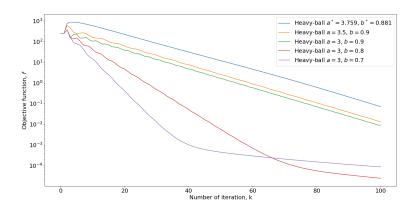


Figure 1: Convergence of Heavy-ball method with different estimates of  $\alpha$ ,  $\beta$ ,  $A \in \mathbb{R}^{n \times n}$ ,  $n = 10^3$ ,  $\varkappa = 10^3$ .

# Aim and Objectives

### Heavy-ball method

- analysis of non-monotonic behavior
- 2 construction of the Lyapunov function
- implementation of Heavy-ball method for the State estimation problem in power systems

## Non-monotonic behavior

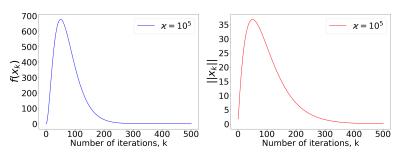


Figure 2: Dependence of  $f(x_k)$  and  $||x_k||$  on the number of iterations k.

#### "Peak effect"

- $A = \operatorname{diag}(1, 10^5), x_0 = x_1 = (1, 1)^T$
- $\alpha^*, \beta^*$  optimal parameters



#### Non-monotonic behavior

## Form of a linear difference equation

$$x_{k+1} = x_k ((1+\beta)I - \alpha A) - \beta x_{k-1}$$

$$Ae_i = \lambda_i e_i$$

$$x_{k+1}^i = ax_k^i + bx_{k-1}^i$$

$$a = (1+\beta - \alpha \lambda_i), \quad b = -\beta$$

# Proposition ("Peak effect")

Assume that  $f(x) = \frac{1}{2} (Ax, x)$ ,  $\mu I \leq A \leq LI$ , where  $\mu$ , L - strong convexity and Lipschitz constants. There are initial conditions  $\|x_0\| \leq 1$ ,  $\|x_1\| \leq 1$ ,  $x_0, x_1 \in R^n$ , which lead to a peak effect in Heavy-ball method with optimal parameters  $\alpha^*, \beta^*$ :

$$\max_{k} ||x_k|| \ge \frac{\sqrt{\varkappa}}{2e}.$$

## Non-monotonic behavior

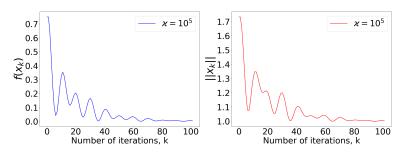


Figure 3: Dependence of  $f(x_k)$  and  $||x_k||$  on the number of iterations k.

- $A = \operatorname{diag}(1, 10^5), \ x_0 = x_1 = (1, 1)^T$
- $\alpha \neq \alpha^*, \beta \neq \beta^*$  non-optimal parameters



# Heavy-ball method (Continuous case)

## Continuous case

$$\ddot{x} + a\dot{x} + b\nabla f(x) = 0$$

- $\begin{array}{l}
  \bullet \ \dot{x} = y \\
  \dot{y} = -ay b\nabla f(x)
  \end{array}$
- a, b > 0

## Lyapunov function (total energy)

$$V(x,y) = f(x) + \frac{1}{2h}||y||^2, \quad \dot{V}(x,y) \le 0$$

#### Upper bound

$$||x(t) - x^*|| \le \sqrt{\varkappa} ||x(0) - x^*||$$

# Construction of the Lyapunov function

### Heavy-ball method (Discrete case)

$$x_{k+1} = x_k - \alpha \nabla f(x_k) + \beta (x_k - x_{k-1})$$

 $\alpha, \beta > 0$  - method parameters

## Theorem (Lyapunov function)

Assume that  $f \in \mathscr{F}_L^{1,1}$  and that  $\alpha \in (0, \frac{1}{L})$ ,  $\beta \in [0, \sqrt{(1 - \alpha L)}]$ . Then for any initial conditions  $x_0, x_1 \in R^n$  the following function

$$V(x_k) = f(x_k) + \frac{1 - \alpha L}{2\alpha} ||x_k - x_{k-1}||^2$$

is a Lyapunov function for the discrete case of the Heavy-ball method

$$V(x_k) \leq V(x_{k-1}).$$

## Monotonic behavior

## Lyapunov function

$$V(x_k) = f(x_k) + \frac{1 - \alpha L}{2\alpha} ||x_k - x_{k-1}||^2$$

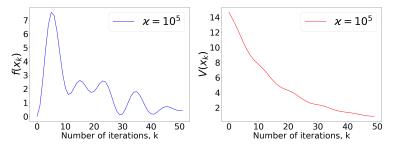


Figure 4: The behavior of objective function  $f(x_k)$  and Lyapunov function  $V(x_k)$  depending on the number of iterations k.

### Results

#### Lyapunov function

$$V(x_k) = f(x_k) + \frac{1 - \alpha L}{2\alpha} ||x_k - x_{k-1}||^2$$

The conditions for the parameters:

$$0 < \alpha < \frac{1}{L} \qquad 0 \le \beta \le \sqrt{1 - \alpha L}$$

- $\bullet$  it is not necessary to know the constant of strong convexity  $\mu$
- adaptive algorithm without knowledge of the Lipschitz constant L



Marina Danilova (MIPT) Heavy-ball method

## Results

#### Theorem (global convergence)

Assume that  $f \in \mathscr{F}_{\mu,L}^{1,1}$  in  $0 \leq \mu \leq L$  and that

$$\alpha \in (0, \frac{1}{L}), \beta \in [0, \sqrt{(1 - \alpha L)(1 - \alpha \mu)}].$$

Then, the Heavy-ball method converges linearly for any initial conditions  $x_0 = x_1 \in \mathbb{R}^n$ :

$$||x_k - x^*|| \le \sqrt{\varkappa} q^k ||x_0 - x^*||,$$

where  $q = (1 - \alpha \mu)$ .



# Practical part

## State estimation of power system

Calculating an approximation for the unknown state variables in the system obtained from imperfect measurements.

#### State variables

- V voltage magnitude
- ullet  $\theta$  voltage phase angle

#### State estimation

$$z = \begin{pmatrix} z_1 \\ \dots \\ z_m \end{pmatrix} - \text{measurements } (P, Q, V, \theta)$$

$$x = \begin{pmatrix} x_1 \\ \dots \\ x_n \end{pmatrix}$$
 - state variables  $(V, \theta)$ 

$$h(x) = \begin{pmatrix} h_1(x_1, ... x_n) \\ ... \\ h_m(x_1, ... x_n) \end{pmatrix}$$
 - non-linear functions (nodal equations)

The objective function to be minimized is

$$\min_{x} J(x) = \min_{x} \sum_{i=1}^{m} \frac{(z_i - h_i(x))^2}{\sigma_i^2}$$

 $\sigma^2$  - i-th measurement variance .



# Non-monotonicity effect

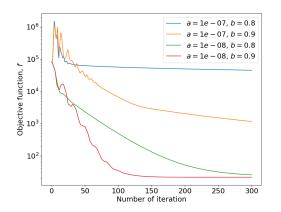


Figure 5: Convergence of HB method with different estimates of  $\alpha,\ \beta$  for IEEE 14-Bus power system.

# Lyapunov function for state estimation

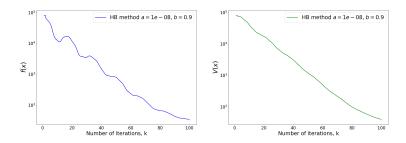


Figure 6: The behavior of objective function  $f(x_k)$  and Lyapunov function  $V(x_k)$  with parameters  $\alpha = 1e - 08$ ,  $\beta = 0.9$  for IEEE 14-Bus power system.

#### Future research

- Improving the Lyapunov function
- Developing an adaptive algorithm
- Considering the Nesterov's accelerated gradient method

#### References

- Boris Polyak, Marina Danilova and Anastasiya Kulakova.
   Non-asymptotic Behavior of Multi-Step Iterative Methods.
   ICDEA 2018.
- Boris Polyak. Some methods of speeding up the convergence of iteration methods. USSR Computational Mathematics and Mathematical Physics, 4:5:1-17, 1964.
- Boris Polyak and Pavel Shcherbakov. Lyapunov functions: An optimization theory perspective. *IFAC-Papers OnLine*, 50.1: 7456 7461, 2017.
- Yurii Nesterov. A method for unconstrained convex minimization problem with the rate of convergence O(1/k2). Soviet Mathematical Doklady, 27: 372 376, 1983.
- Pontus Giselsson and Stephen Boyd. Monotonicity and restart in fast gradient methods. In Decision and Control (CDC), 2014 IEEE 53rd Annual Conference on. 2014.

Thank you for your attention!