

# Lecture 11: Average Sub-Gradient Method as a Version of Integral Sliding Mode Control

## Plan of presentation

- Where it was published
- Model description and problem setting
- Accepted assumptions
- Problem formulation
- Examples of loss-functions
- Desired regime
- Functional convergence
- Main theorem on ASG robust controller

# Where it was published

- 1 Poznyak, A.S.; Nazin A.V.; Alazki H., Integral Sliding Mode Convex Optimization in Uncertain Lagrangian Systems Driven by PMDC Motors: Averaged Subgradient Approach. *IEEE Transactions on Automatic Control*, 2021, 66(9), 4267–4273.
- 2 Alexander Nazin, Hussain Alazki, and Alexander Poznyak, Robust Tracking as Constrained Optimization by Uncertain Dynamic Plant: Mirror Descent Method and ASG – Version of Integral Sliding Mode Control. *Mathematics 2023, MDPI* (to be published).
- 3 A.V. Nazin and A. S. Poznyak, Non-quadratic proxy functions in Mirror Descent Method applied to designing of robust controllers for nonlinear dynamic systems with uncertainty. *Computational Mathematics and Mathematical Physics*, Springer (to be published).

# Model description and problem setting

- Here we will deal with the construction of a feedback, which designing is very close to the ISM approach, together with the, so-called, **Averaged Sub-Gradient (ASG)** Technique.
- Consider the dynamic model of a Lagrangian mechanical system with  $n$ -degrees of freedom in the standard form given by the following set of differential equations:

$$\boxed{D(q(t)) \ddot{q}(t) + C(q(t), \dot{q}(t)) \dot{q}(t) + G(q(t)) = \tau(t) + \vartheta(t),} \quad (1)$$

where  $q(t), \dot{q}(t) \in R^n$  are the state vectors (generalized coordinates and their velocities,  $t \geq 0$ ),  $\tau(t) \in R^n$  is a vector of external torques (control) acting to the mechanical system, and  $\vartheta(t) \in R^n$  is the disturbance (or uncertainty) vector.

# Model of tracking error

If we wish to resolve the tracking problem for the given nominal trajectory  $q^*(t)$ , then we can represent the dynamics of the controlled plant **in deviation coordinates**  $\delta(t) := q(t) - q^*(t)$  as follows

$$\tilde{D}(\delta(t)) \ddot{\delta}(t) = \tau(t) + \vartheta(t) - \tilde{C}(\delta(t), \dot{\delta}(t)) \dot{\delta}(t) - \tilde{G}(\delta(t)) \quad (2)$$

with

$$\begin{aligned} \tilde{D}(\delta) &:= D(\delta + q^*), \\ \tilde{C}(\delta, \dot{\delta}) &:= C(\delta + q^*, \dot{\delta} + \dot{q}^*), \\ \tilde{G}(\delta) &:= G(\delta + q^*). \end{aligned}$$

# Model of tracking error

Notice that the deviation dynamics (2) may be represented as (omitting the time-argument)

$$\ddot{\delta} = \tilde{D}^{-1}(\delta) \tau + \tilde{D}^{-1}(\delta) \tilde{\zeta}, \quad (3)$$

or, equivalently, as

$$\left. \begin{aligned} \delta_1 &:= \delta, \\ \dot{\delta}_1 &= \delta_2, \\ \dot{\delta}_2 &= \tilde{D}^{-1}(\delta_1) \tau + \tilde{D}^{-1}(\delta_1) \tilde{\zeta}. \end{aligned} \right\} \quad (4)$$

- A1. The vector of generalized coordinate  $q(t)$  and its derivative  $\dot{q}(t)$  are measurable on-line during the process.
- A2. The matrix  $D(q)$  is supposed to be known and invertible (the usual property of any mechanical system).
- A3. The uncertain term

$$\xi(t) := \vartheta(t) - \tilde{C}(\delta(t), \dot{\delta}(t)) \dot{\delta}(t) - \tilde{G}(\delta(t)) \quad (5)$$

is admitted to be unknown and unmeasurable, but is bounded as

$$\|\xi(t)\| \leq c + c_0 \|\delta(t)\| + c_1 \|\dot{\delta}(t)\|, \quad c, c_0, c_1 \geq 0. \quad (6)$$

- A4. The loss function  $F : \mathbb{R}^n \rightarrow \mathbb{R}^1$ , characterizing the quality of a controlled process, is assumed to be unknown, convex (not obligatory, strongly convex), differentiable for almost all  $\delta \in \mathbb{R}^n$  (the Radamacher theorem) and its sub-gradient  $a(\delta)$  is supposed to be measurable and bounded at any point  $\delta_1$ , that is,

$$\|a(\delta(t))\| \leq d_g < \infty,$$

and the reaction  $a(\delta)$  is available for any argument  $\delta \in \mathbb{R}^n$ .

- A5. The minimum of the loss function  $F(\delta)$  exists, namely,

$$F^* = \min_{\delta \in \mathbb{R}^n} F(\delta) > -\infty.$$

## Problem

*Under the assumptions A1-A3 we need to design a control strategy  $\tau(t)$  as a feedback  $\tau(\delta(\cdot))$ , which provides the **functional convergence** of the cost function  $F(\delta(t))$  to its minimum value  $F^*$ , in the presence of uncertainties  $\zeta(t)$ , that is, to guarantee*

$$\boxed{F(\delta(t)) \xrightarrow{t \rightarrow \infty} \inf_{\delta \in \mathbb{R}^n} F(\delta) = F^*,} \quad (7)$$

*supposing that the current **sub-gradient**  $a(\delta(t))$  of the convex function  $F(\delta)$ , to be optimized, is available on-line.*



# Examples of loss-functions

The convex (not obligatory strongly) loss function  $F : \mathbb{R}^n \rightarrow \mathbb{R}^1$  defines the quality of control actions  $\{\tau(t)\}_{t \geq 0}$  in the point  $\delta(t)$ . For example, the following two functions belong to the considered class of the convex loss functions to be optimized:

1

$$F(\delta) = \sum_{i=1}^n |\delta_i|, \quad a_i(\delta) = \text{sign}(\delta_i),$$

2

$$F(\delta) = \sum_{i=1}^n |\delta_i|_{\varepsilon}^+, \quad |z|_{\varepsilon}^+ := \begin{cases} z - \varepsilon & \text{if } z \geq \varepsilon \\ -z - \varepsilon & \text{if } z \leq -\varepsilon \\ 0 & \text{if } |z| < \varepsilon \end{cases},$$

$$a_i(\delta_i) = \begin{cases} 1 & \text{if } \delta_i \geq \varepsilon \\ -1 & \text{if } \delta_i \leq -\varepsilon \\ (-1, 1) & \text{if } |\delta_i| < \varepsilon \end{cases} = \text{sign}(|\delta| - \varepsilon).$$

In both these examples  $F^* = F(0) = 0$ .

# Desired dynamics and its properties

## Auxiliary sliding variable

Define the vector function  $s(t) \in \mathbb{R}^n$ , which from now on and throughout this lecture will be referred to as "sliding variable":

$$\left. \begin{aligned} s(t) &= \dot{\delta}(t) + \frac{\delta(t) + \eta}{t + \theta} + \tilde{G}(t), \quad \eta = \text{const} \in \mathbb{R}^n, \\ \tilde{G}(t) &:= \frac{1}{t + \theta} \int_{\tau=t_0}^t a(\delta(\tau)) d\tau, \quad \theta > 0, \\ a(\delta_1(\tau)) &\in \partial F(\delta_1(\tau)) \end{aligned} \right\} \quad (8)$$

Here  $\delta(t) := q(t) - q^*(t) \in \mathbb{R}^n$ ,  $\eta$  is a constant vector and  $\tilde{G}(t)$  is the averaged subgradient (ASG) of the function  $F(\delta(t))$  (7). Note that the sliding variable  $s(t)$  contains the integral term which is physically measurable.

# Desired dynamics

Define the desired ASG dynamics as

$$\boxed{s(t) = \dot{s}(t) = 0, t \geq t_0,} \quad (9)$$

which corresponds exactly to the situation when the sliding variable  $s(t)$  is equal to zero for all  $t \geq t_0$ . Below we will show why the dynamic (9) is called a desired. Since

$$\left. \begin{aligned} (t + \theta) s(t) = (t + \theta) \dot{\delta}(t) + \delta(t) + \eta = \zeta(t), \\ \dot{\zeta}(t) = -a(\delta(t)), \zeta(t_0) = 0, \end{aligned} \right\} \quad (10)$$

in the desired regime (9) we have

$$\left. \begin{aligned} (t + \theta) \dot{\delta}(t) + \delta(t) + \eta = \zeta(t), \quad t \geq t_0 \geq 0, \\ t_0 \text{ is the moment when the desired dynamics may begin.} \end{aligned} \right\} \quad (11)$$

# Why this regime is referred to as "desired" ?

## Lemma

For the variable  $\delta(t)$ , satisfying the ideal dynamics (9), with any  $\theta > 0$  and  $\eta$ , for all  $t \geq t_0 \geq 0$  the following inequality is guaranteed:

$$F(\delta(t)) - F^* \leq \frac{\Phi(t_0)}{t + \theta} \xrightarrow{t \rightarrow \infty} 0, \quad (12)$$

where

$$\Phi(t_0) = \Phi(\delta(t_0), \theta, \eta) := (t_0 + \theta) F(\delta(t_0)) - F^* + \frac{1}{2} \|\delta^* - \eta\|^2, \quad (13)$$

and

$$\begin{aligned} \delta^* \in \operatorname{Arg} \inf_{\delta \in \mathbb{R}^n} F(\delta) \\ \vdots \\ (\delta^* \text{ may be not unique}). \end{aligned} \quad (14)$$

# Proof of Lemma on Functional convergence (1)

Proof.

Defining  $\mu(t) := t + \theta$  we have

$$\begin{aligned} \frac{d}{dt} \left[ \frac{1}{2} \|\zeta(t)\|^2 - \zeta^T(t) \delta^* \right] &= \dot{\zeta}^T(t) (\zeta(t) - \delta^*) = \\ &= -a^T(\delta(t)) [\mu(t) \dot{\delta}(t) + \delta(t) + \eta - \delta^*] = \\ &= -a^T(\delta(t)) (\delta(t) - \delta^*) - a^T(\delta(t)) (\mu(t) \dot{\delta}(t) + \eta). \end{aligned}$$

Using the inequality  $(\delta - \delta^*)^T a(\delta) \geq F(\delta) - F^*$ , valid for convex (not obligatory strongly convex) functions in the first term on the right side, and applying the identity  $a^T(\delta(t)) \dot{\delta}(t) = \frac{d}{dt} [F(\delta(t)) - F^*]$ , we get

$$\begin{aligned} \frac{d}{dt} \left[ \frac{1}{2} \|\zeta(t)\|^2 - \zeta^T(t) \delta^* \right] &\leq - [F(\delta(t)) - F^*] \\ &\quad - \mu(t) \frac{d}{dt} [F(\delta(t)) - F^*] - a^T(\delta(t)) \eta. \end{aligned}$$

# Proof of Lemma on Functional convergence (2)

## Proof.

Then, integrating the last inequality in the interval  $[t_0, t]$  and applying the formula of integration by parts, we derive

$$\begin{aligned} \int_{\tau=t_0}^t [F(\delta(\tau)) - F^*] d\tau &\leq \frac{1}{2} \left( \|\zeta(t_0)\|^2 - \|\zeta(t)\|^2 \right) + \\ &\quad (\zeta(t) - \zeta(t_0))^T \delta^* - (\mu(t) [F(\delta(t)) - F^*])_{t_0}^t + \\ &\quad \int_{\tau=t_0}^t [F(\delta(\tau)) - F^*] \dot{\mu}(\tau) d\tau - \left[ \int_{\tau=t_0}^t a^T(\delta(\tau)) d\tau \right] \eta. \end{aligned}$$



# Proof of Lemma on Functional convergence (3)

## Proof.

Since  $\dot{\mu}_\tau = 1$ , the above inequality becomes

$$\left. \begin{aligned} & \mu(t) [F(\delta(t)) - F^*] \leq \mu(t_0) [F(\delta(t_0)) - F^*] + \\ & \frac{1}{2} \left( \|\zeta(t_0)\|^2 - \|\zeta(t)\|^2 \right) + (\zeta(t) - \zeta(t_0))^T \delta^* + \zeta^T(t) \eta = \\ & (t_0 + \theta) [F(\delta(t_0)) - F^*] + \left( \frac{1}{2} \|\zeta(t_0)\|^2 - \zeta^T(t_0) \delta^* \right) + \\ & \frac{1}{2} \|\delta^* - \eta\|^2 - \frac{1}{2} \underbrace{\left[ \|\zeta(t)\|^2 - 2\zeta^T(t) (\delta^* - \eta) + \|\delta^* - \eta\|^2 \right]}_{\|\zeta(t) - (\delta^* - \eta)\|^2} \end{aligned} \right\} \quad (15)$$
$$\begin{aligned} & \leq (t_0 + \theta) [F(\delta(t_0)) - F^*] - \frac{1}{2} \|\zeta(t) - (\delta^* - \eta)\|^2 + \\ & \left( \frac{1}{2} \|\zeta(t_0)\|^2 - \zeta^T(t_0) \delta^* \right) + \frac{1}{2} \|\delta^* - \eta\|^2 \leq \Phi_{t_0}, \end{aligned}$$

from which we obtain (13). Lemma is proved. □

# Important comment (1)

## Remark

*The parameter  $\eta$  will be chosen below in such a way that the desired optimization regime starts from the beginning of the process, namely, when,  $t_0 = 0$ .*



## Important comment (2)

### Corollary

*In the partial case when*

$$\delta^* = 0, \quad t_0 = 0 \text{ and } F^* = 0$$

*the formula (13) becomes*

$$\Phi(t_0) = \Phi(\delta(t_0), \theta, \eta) := \theta F(\delta(0)) + \frac{1}{2} \|\eta\|^2. \quad (16)$$

# Main theorem on ASG robust controller

## Theorem

Under assumptions 1-5 the ISM robust controller

$$\left. \begin{aligned} \tau(t) &= \tilde{D}(\delta(t)) [-k_t \text{SIGN}(s(t)) + u_{comp}(t)], \\ u_{comp}(t) &= -p_t^{reali}, \\ k_t &= \|\tilde{D}^{-1}(\delta(t))\| (c + c_0 \|\delta(t)\| + c_1 \|\dot{\delta}(t)\|) + \rho_0, \rho_0 > 0, \end{aligned} \right\} \quad (17)$$

where

$$p_t^{reali} := \frac{1}{t + \theta} \left( \dot{\delta}(t) - \frac{\delta(t) + \eta}{t + \theta} - \tilde{G}(t) + a(\delta(t)) \right) \quad (18)$$

with

$$\eta = -\theta \delta_{2,0} - \delta_{1,0} \quad (19)$$

guarantees the functional convergence (12) from  $t_0 = 0$ .

# Proof of Main Theorem (1)

## Proof.

In view of the assumption A2 we have

$$\left. \begin{aligned} \delta(t) &:= q(t) - q^*(t), \quad \dot{\delta}(t) = \dot{q}(t) - \dot{q}^*(t), \\ \ddot{\delta}(t) &= \tilde{D}^{-1}(\delta(t)) \tau(t) + \tilde{D}^{-1}(\delta(t)) \zeta(t). \end{aligned} \right\}$$

For the Lyapunov function  $V(s) = \frac{1}{2} s^T s$  we have

$$\left. \begin{aligned} \dot{V}(s(t)) &= s^T(t) \dot{s}(t) = \\ s^T(t) &\left( \ddot{\delta}(t) + \frac{\dot{\delta}(t)}{t+\theta} - \frac{\delta(t)+\eta}{(t+\theta)^2} - \frac{1}{t+\theta} \tilde{G}(t) + \frac{1}{t+\theta} a(\delta(t)) \right) = \\ &s^T(t) \left( \tilde{D}^{-1}(\delta(t)) \tau(t) + \tilde{D}^{-1}(\delta(t)) \zeta(t) \right) + \\ &s^T(t) \left( \frac{1}{t+\theta} \left( \dot{\delta}(t) - \frac{\delta(t)+\eta}{t+\theta} - \tilde{G}(t) + a(\delta(t)) \right) \right) = \\ s^T(t) p_t^{\text{reali}} &+ s^T(t) \tilde{D}^{-1}(\delta(t)) \tau(t) + s^T(t) \tilde{D}^{-1}(\delta(t)) \zeta(t). \end{aligned} \right\} \quad (20)$$



## Proof of Main Theorem (2)

Proof.

Selecting  $\tau$  as in (17) for the second term in (20) we get

$$\left. \begin{aligned} \dot{V}(s_t) &= -k_t s^\top(t) \text{SIGN}(s(t)) + s^\top(t) \tilde{D}^{-1}(\delta(t)) \zeta(t) \\ &\leq -k_t \sum_{i=1}^n |s_i(t)| + \|s(t)\| \|\tilde{D}^{-1}(\delta(t))\| \|\zeta(t)\| \end{aligned} \right\} \quad (21)$$

□

# Proof of Main Theorem (3)

## Proof.

Taking into account that  $\sum_{i=1}^n |s_i(t)| \geq \|s(t)\|$  and, in view of (6) and (21), we derive

$$\begin{aligned}\dot{V}(s(t)) &\leq -k_t \|s(t)\| + \|s(t)\| \|\tilde{D}^{-1}(\delta(t))\| (c + c_0 \|\delta(t)\| + c_1 \|\dot{\delta}(t)\|) \\ &= -\rho_0 \|s(t)\| = -\sqrt{2}\rho_0 \sqrt{V(s(t))},\end{aligned}$$

implying  $2 \left( \sqrt{V(s(t))} - \sqrt{V(s(t_0))} \right) \leq -\sqrt{2}\rho_0 t$  and

$$0 \leq \sqrt{V(s(t))} \leq \sqrt{V(s(t_0))} - \frac{\rho_0}{\sqrt{2}} t,$$

which leads to the conclusion that for all  $t \geq t_{reach} := \frac{1}{\rho_0} \sqrt{2V(s_{t_0})} = \frac{\|s_{t_0}\|}{\rho_0}$

we have that  $V(s(t))=0$  and  $s(t)=0$ . □

# Proof of Main Theorem (4)

## Proof.

To make the reaching time  $t_{reach} = 0$  it is sufficient to guarantee that  $s_{t_0=0} = 0$ . But since by (10)

$$\begin{aligned}(t + \theta) s(t) &= (t + \theta) \dot{\delta}(t) + \delta(t) + \eta = \zeta(t), \\(t_0 + \theta) s(t_0) &= (t_0 + \theta) \dot{\delta}(t_0) + \delta(t_0) + \eta = \zeta(t_0) \\s_{t_0} &= \dot{\delta}_{t_0} + \frac{\delta_{t_0} + \eta}{t_0 + \theta},\end{aligned}$$

we need to fulfill the condition  $s_{t_0=0} = \dot{\delta}_{t_0=0} + \frac{\delta_{t_0=0} + \eta}{\theta} = 0$ , which is possible if take  $\eta$  as in (19), providing

$$t_{reach} = \frac{\|s_{t_0=0}\|}{\rho_0} = 0.$$

Theorem is proven. □