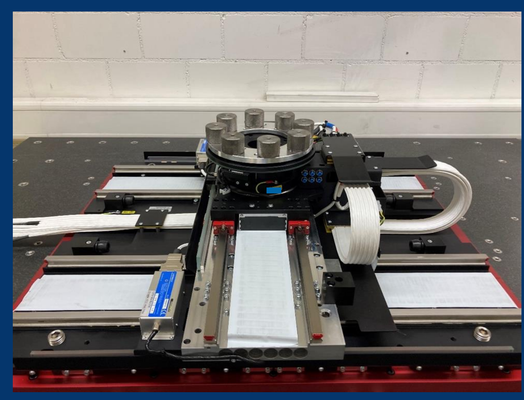
Adaptive Bayesian Optimization for High-Precision Motion Systems



Christopher König[1], Raamadaas Krishnadas[1], Efe C. Balta[1,2] Alisa Rupenyan[3]

[1] inspire AG, Zurich, Switzerland
[2] Automatic Control Laboratory, Dept. of Electrical Engineering and Inoformation Technology, ETH Zürich, Zurich, Switzerland
[3] Centre for Artificial Intelligence (CAI), ZHAW School on Engineering, Zurich University for Applied Sciences, Zurich, Switzerland

Email: alisa.rupenyan@zhaw.ch

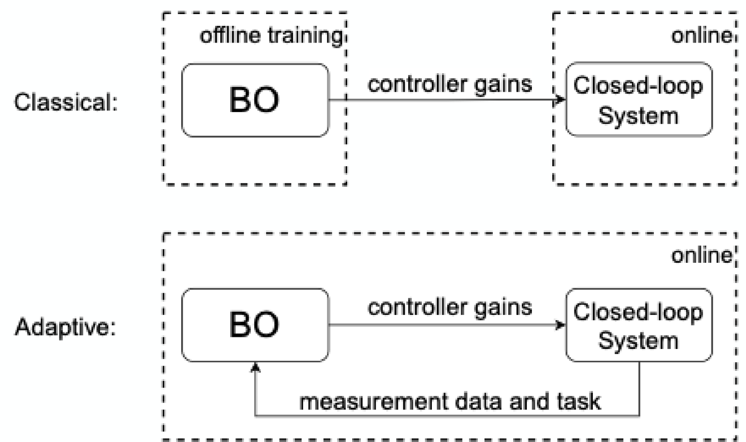
Motivation

In manufacturing and industrial environments, environment or equipment is subject to change. By using a method based on Bayesian Optimization and safe exploration, our method optimizes continuously desired parameters based on the prescribed system performance. We include input and output constraints, which are satisfied throughout the optimization procedure. Therefore, the method is suitable for use in practical systems where safety or operational constraints are of concern. We include contextual information, using task parameters, which makes the optimization flexible.

Objectives

i. Safe optimization
ii. Computational efficiency (fast motion system)
iii. Adaptive to internal and external changes while resecting (unknown) constraints
iv. Works for high-performance motion systems

Adaptive Goal-oriented Safe Exploration (GoOSE) with constraints



$$\min_{x\in\mathcal{X}}\{f(x)\mid q(x)\le c\ \&\ x_\tau = x_{\tau,t}\}$$

$$\{x \mid q(x) \le c\} \neq \emptyset$$

$$x_\tau \in \mathcal{X}_{x_\tau}$$

context

We use Gaussian Process models to model the cost f(x) and the constraint q(x).

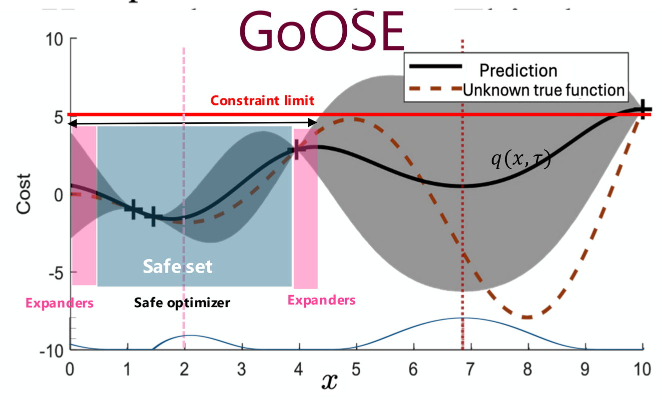
$$\mathrm{lcb}_t(x) = \mu_t(x) - \beta^{f/q}\sigma_t(x)$$

$$\mathrm{ucb}_t(x) = \mu_t(x) + \beta^{f/q}\sigma_t(x)$$

Mult-task kernel

$$k_{\text{multi}}((x_{\text{opt}}, x_\tau), (x'_{\text{opt}}, x'_\tau)) = k_\tau(x_\tau, x'_\tau)\otimes k(x_{\text{opt}}, x'_{\text{opt}})$$

GoOSE

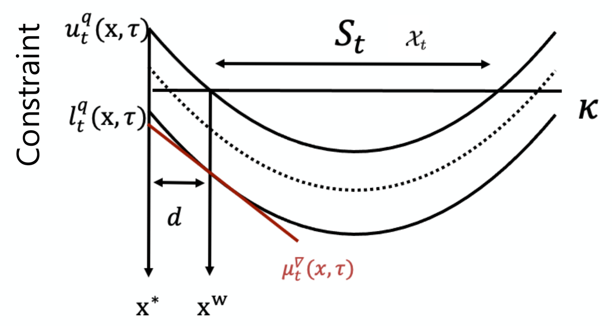


$q(\mathcal{X}_0) < c$ Safe seed

$\mathcal{X}_t = \{x \in \mathcal{X} \mid \mathrm{ucb}^q_t(x) \le c\}$, Pessimistic set

$\mathcal{X}^{opt}_t = \{x \in \mathcal{X} \mid \exists \bar{x} \in W_t,\ \text{s.t. } g^t_\epsilon(\bar{x}, x) > 0\}$ Optimistic set

$W_t \subset \mathcal{X}_t$ Expanders set



$$g^t_\epsilon(\bar{x}, x) = \mathbb{I}\left[\mathrm{lcb}^q_t(\bar{x}) + \left\|\mu^\nabla_t(\bar{x})\right\|_\infty d(\bar{x}, x) + \epsilon \le c\right]$$

$$|\mathrm{ucb}^q_t(x) - \mathrm{lcb}^q_t(x)| > \epsilon$$

Evaluation of the expander, minimizing the distance between the evaluated point and the (potential) optimizer

We calculate each set explicitly during each BO iteration, following discretization of the expanders domain.

Requirements for run-to-run optimization in real time:

- Fast computation (update before next move, 50 ms)
- Maintain safety (cannot excite vibrations via aggressive parameters)
- Adapt to different contexts (different payload, step size, drifts)

C. König, M. Turchetta, J. Lygeros, A. Rupenyan and A. Krause, "Safe and Efficient Model-free Adaptive Control via Bayesian Optimization," *2021 IEEE International Conference on Robotics and Automation (ICRA)*, Xi'an, China, 2021,

Modified GoOSE approach

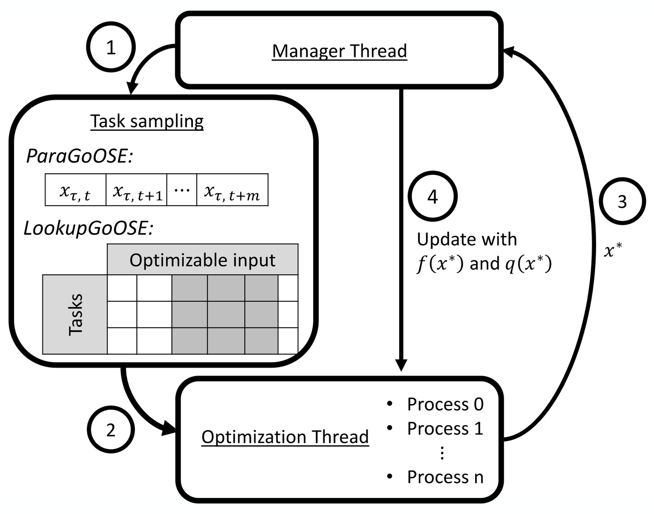
Make it fast

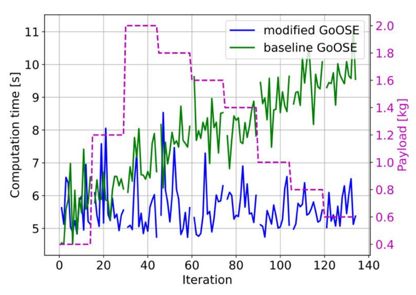
- Remove expanders search
- Make the optimizers safe and expansive
- Simultaneous update for all possible contexts τ

- Lower bound on the cost f $\{\exists\xi \in \mathbb{R} \mid f(x) \ge \xi, \forall x \in \mathcal{X}\}$
- Conditions on the cost and constraint priors (parameter tuning)

$\mu^q_0(x) + \beta^q\sigma^q_v > c \quad \forall x \in \mathcal{X}$ Safety in the presence of uncertainty (1)

$\mu^f_0(x) - \beta^f\sigma^f_v \le \xi \quad \forall x \in \mathcal{X}$ Expansion in the presence of uncertainty (2)





Parallel computation schemes for fast optimization

- ParaGoOSE: Predicts a horizon of upcoming task parameters. Parallelizes optimization by pre-computing optimizers for those predicted future tasks across multiple processes.

$$x_t = \operatorname*{argmin}_{x\in\mathcal{X}_t} \mathrm{lcb}^f_t(x)$$ Compute for each task in parallel

- LookupGoOSE: Maintains a discretized lookup table of pre-computed optimizers across the entire task parameter space and updates neighborhoods around newly observed tasks in parallel.

$$x_\tau \in \mathcal{X}_{x_\tau} : |x_\tau - x_{\tau,t}| < k\Delta x_\tau,\ k > 0$$

Neighborhood update

Implementation:

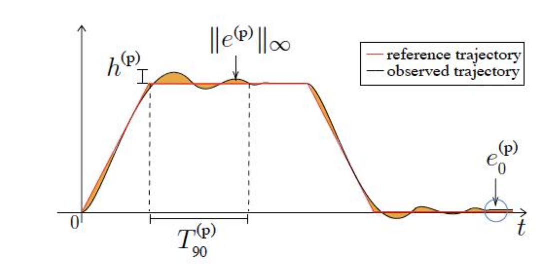
Active phase: Explores by adding new experimental data to update the GP models, using lower confidence bound (lcb) acquisition (1).

$$x_t = \operatorname*{argmin}_{x\in\mathcal{X}_t} \mathrm{lcb}^f_t(x)$$

Passive phase: Exploits the learned GP models without updating them, using upper confidence bound (ucb) to find the pessimistic optimum (2) until constraint violation or task change triggers restart.

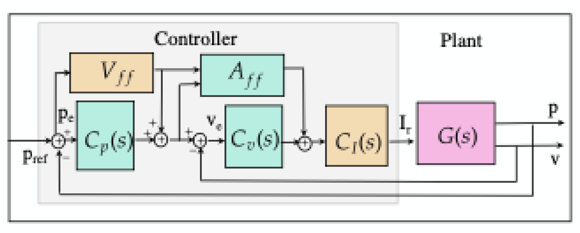
$$x^* = \operatorname*{argmin}_{x\in\mathcal{X}_t} \mathrm{ucb}^f_t(x)$$

Optimization set-up

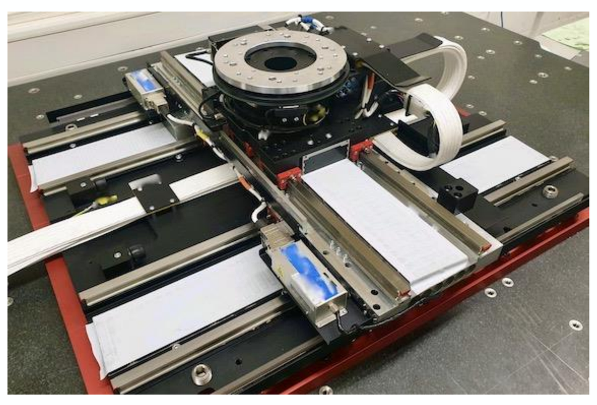


$$F^{(p)} := [h^{(p)}, \bar{h}^{(p)}, T^{(p)}_{90}, \|e^{(p)}\|_\infty, e^{(p)}_{\text{ITAE}}, e^{(p)}_{\text{ss}}, e^{(p)}_0]^\top$$

Improve control performance, reduce settling error

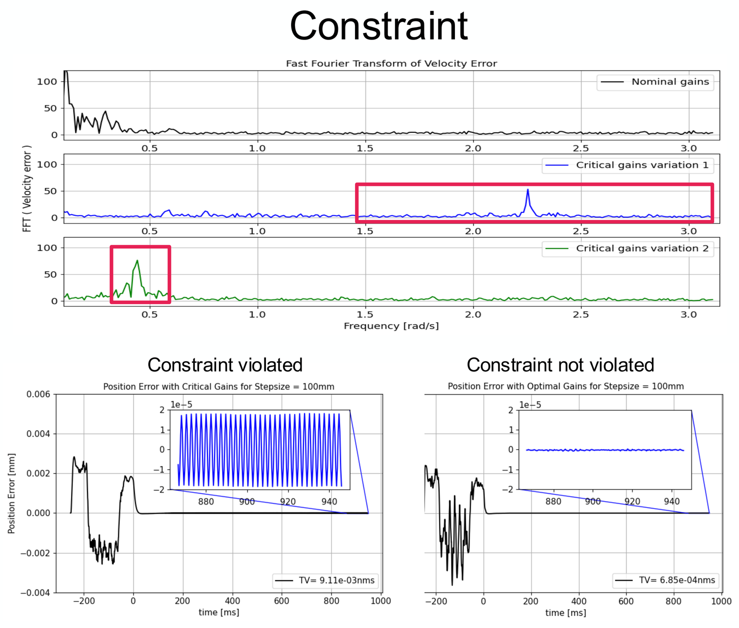


$C_p(s) = P_{kp} \quad C_v(s) = V_{kp} + V_{ki}/s$

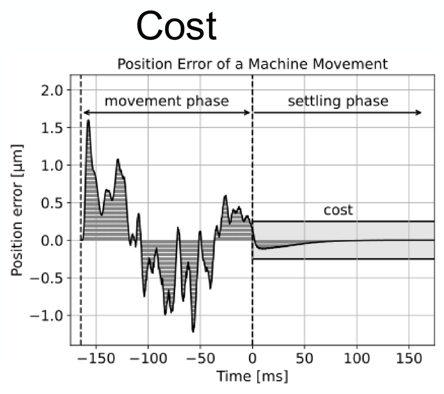


Optimize control parameters $P_{kp}, V_{kp}, V_{ki}, A_{ff}$

Constraint



Cost

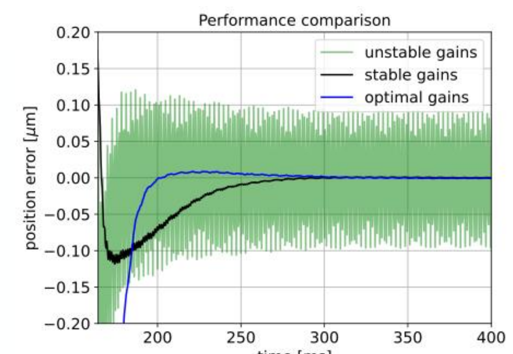


$$f(x) = \frac{1}{n_P - n_s}\sum_{i=n_s}^{n_P} |\xi(i, n_s)p_e(t_i)|,$$ Position error

$$q(x) = \max|\mathcal{F}[\xi(i, n_s)v_e(t_i)](x, f = f_1)|$$ Velocity error

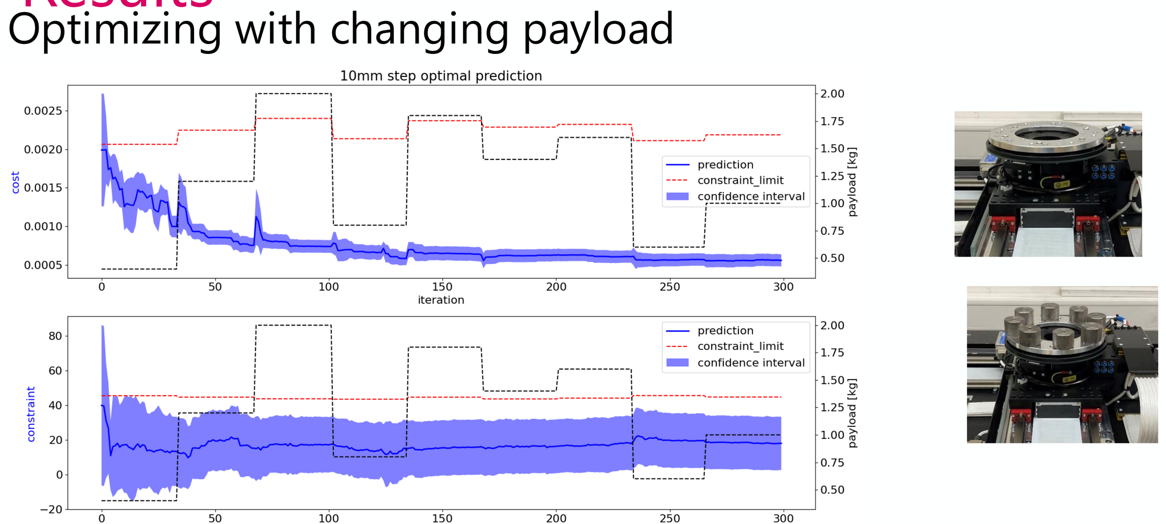
$$f_1 = [140\text{Hz}, 1250\text{Hz}],$$

$$\xi(i, n_s) = 1 - \frac{1}{1 + \exp(-(i - n_s - 150)/10)}$$ Left-sided sigmoid function

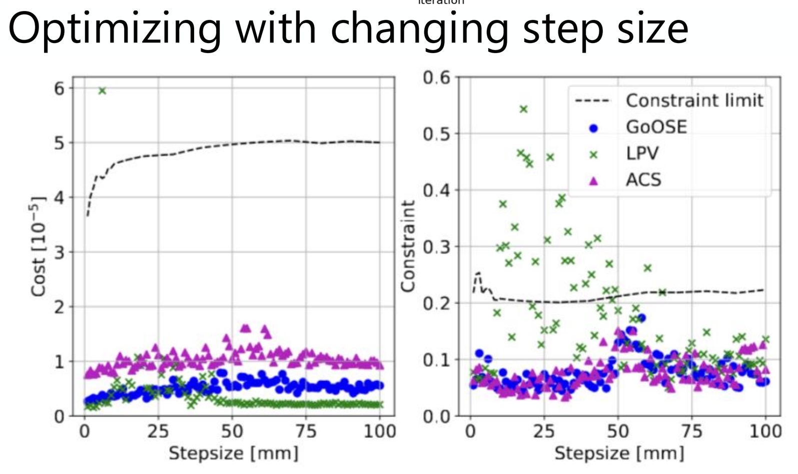


Results

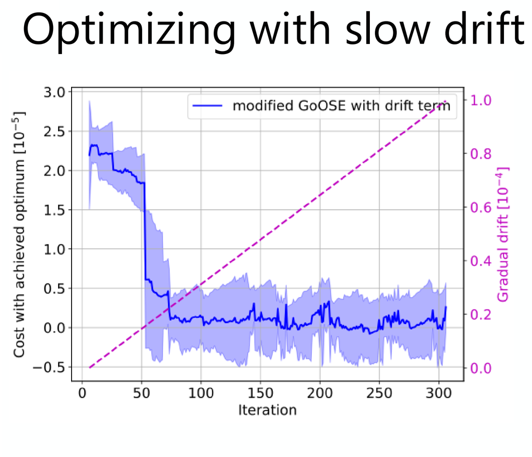
Optimizing with changing payload



Optimizing with changing step size



Optimizing with slow drift



Achieved: Fast, adaptive, safe run-to-run optimization for high-performance motion systems.

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