Safety-Aware Robot Damage Recovery Using Constrained Bayesian Optimization and Simulated Priors
Vaios Papaspyros, Konstantinos Chatzilygeroudis, Vassilis Vassiliades, Jean-Baptiste Mouret

To cite this version:
Vaios Papaspyros, Konstantinos Chatzilygeroudis, Vassilis Vassiliades, Jean-Baptiste Mouret. Safety-Aware Robot Damage Recovery Using Constrained Bayesian Optimization and Simulated Priors. Bayesian Optimization: Black-box Optimization and Beyond (workshop at NIPS), 2016, Barcelone, Spain. hal-01407757

HAL Id: hal-01407757
https://inria.hal.science/hal-01407757
Submitted on 2 Dec 2016

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Safety-Aware Robot Damage Recovery
Using Constrained Bayesian Optimization
and Simulated Priors

Vaios Papaspyros$^{1,2,3,4}$ Konstantinos Chatzilygeroudis$^{1,2,3}$ Vassilis Vassiliades$^{1,2,3}$

Jean-Baptiste Mouret$^{1,2,3,\ast}$

Abstract

The recently introduced Intelligent Trial-and-Error (IT&E) algorithm showed that robots can adapt to damage in a matter of a few trials. The success of this algorithm relies on two components: prior knowledge acquired through simulation with an intact robot, and Bayesian optimization (BO) that operates on-line, on the damaged robot. While IT&E leads to fast damage recovery, it does not incorporate any safety constraints that prevent the robot from attempting harmful behaviors. In this work, we address this limitation by replacing the BO component with a constrained BO procedure. We evaluate our approach on a simulated damaged humanoid robot that needs to crawl as fast as possible, while performing as few unsafe trials as possible. We compare our new “safety-aware IT&E” algorithm to IT&E and a multi-objective version of IT&E in which the safety constraints are dealt as separate objectives. Our results show that our algorithm outperforms the other approaches, both in crawling speed within the safe regions and number of unsafe trials.

1 Introduction

Current robots would greatly benefit from being capable of carrying on with their mission when they are damaged, as illustrated by the recent DARPA Robotics Challenge [1, 4]. When damaged, most robots attempt to diagnose the fault and search for a contingency plan; but they could also exploit a reinforcement learning algorithm so that they can find compensatory behaviors without having to "understand" the damage [7, 15]. If they follow this second approach, robots need learning algorithms that are highly data-efficient [5] because too many trials would waste precious time to achieve the mission.

One of the most promising approaches for data-efficient robot damage recovery is the recently introduced Intelligent Trial-and-Error algorithm (IT&E) [7]. It combines two ideas: (1) a Bayesian optimization (BO) algorithm [16] that optimizes a reward function, because it is a generic, data-efficient policy search algorithm [3], and (2) a behavior-performance map generated before the mission with a simulation of the intact robot, which acts both as a prior for the Bayesian optimization algorithm and as a dimension reduction algorithm. This combination allowed a damaged 6-legged robot to find a new gait in about a dozen of trials (less than 2 minutes), and a robotic arm to overcome several blocked joints in a few minutes [7].

Unfortunately, trial-and-error approaches, like IT&E, are likely to damage the robot even more because they will often try behaviors that are too extreme for the mechanical design. More generally,
While recent methods, like SafeOPT [2], tackle this issue successfully, they require an initial safe
where:

This approach leads to short adaptation times in several experiments with damaged robots [7], but

To search for the best behavior on the damaged robot, IT&E alters the classical BO scheme [7] by (1)

The first step of IT&E is to create a low-dimensional behavior-performance map with a simulation of

More precisely, the performance function, \( f(x) \), is modeled as a Gaussian process (GP):

\[
 f(x) \sim GP(m(x), k(x, x')) \\
 p(f(x)|X_{1:t}, x) = N(m(x), \sigma^2(x))
\]

where:

\[
 m(x) = M(x) + k^T(K + \sigma_n^2 I)^{-1}(X_{1:t} - M(x_{1:t}))
\]

\[
 \sigma^2(x) = k(x, x) - k^T(K + \sigma_n^2 I)^{-1}k
\]

and \( K \) is the kernel matrix with \( K_{ij} = k(x_i, x_j) \), \( k = k(X_{1:t}, x) \) and \( X_{1:t} \) the set of observations.

This approach leads to short adaptation times in several experiments with damaged robots [7], but

Interestingly, learning algorithms also push robot simulators to their limits as they often exploit simulation

2 Interestingly, learning algorithms also push robot simulators to their limits as they often exploit simulation inaccuracies.

2 Safety-aware Intelligent Trial & Error Algorithm

The first step of IT&E is to create a low-dimensional behavior-performance map with a simulation of the

Figure 1: Overview of the safety-aware IT&E algorithm. The algorithm first creates a behavior-

performance map through MAP-Elites in simulation. This is fed as prior knowledge to a constrained

BO procedure. The best candidate behavior is executed on the damaged robot while measuring the

contact point forces and crawling speed. Finally, the Gaussian process models are updated.

learning algorithms will push robots to their limits because they focus solely on maximizing the reward intake\(^2\). This issue is especially concerning for expensive prototypes like the iCub robot [13, 17]: these robots are too expensive (around 250k euros for the iCub) and too fragile to try risky behaviors.

While recent methods, like SafeOPT [2], tackle this issue successfully, they require an initial safe set of parameters, that is hard to estimate in an unknown damage setting. In this paper, we extend the IT&E algorithm [7] by adding safety constraints [9] and automatically computing priors over the safety of controller parameters, so that the probability of breaking the robot during the learning process is as low as possible. We evaluate our algorithm using a simulated damaged iCub robot.
We address these issues by introducing a safety-aware IT&E algorithm (sIT&E; see Fig. 1). sIT&E

\[ ECI(\hat{x}) = EI(\hat{x}) \prod_{i=1}^{n} p(c_i(\hat{x}) \geq 0) \]  

where \( \hat{x} \) is the candidate point, \( c_i(\hat{x}), i \in \{1, \ldots, n\} \) are the \( n \) constraint functions and \( EI(\hat{x}) \) is the standard expected improvement [9].

The differences between sIT&E (see Alg.1) and IT&E are as follows: (1) the behavior descriptor in MAP-Elites is augmented with extra dimensions for each safety constraint, so that sIT&E will have a good estimate of the safe regions (i.e., where all inequality safety constraints are fulfilled); for example, these dimensions could be torque or IMU measurements that should not exceed a specific threshold; (2) during the on-line adaptation step, sIT&E optimizes for performance while also guiding the search through the safe regions.

**Algorithm 1 Safety-aware Intelligent Trial-and-Error (sIT&E)**

**procedure** SIT&E

Before mission (intact robot in simulation):

Create Behavior-Performance Map via MAP-Elites storing safety related information

while in mission do

if significant performance drop then

Adaptation Step (via M-CBO Algorithm)

**procedure** MAP-BASED CONSTRAINED BAYESIAN OPTIMIZATION (M-CBO)

\( \forall x \in map : \)

\[ p(f(x)|x) = N(m(x), k(x,x)) \]

\[ p(c_i(x)|x) = N(m_c(x), k_c(x,x)), i \in \{1, \ldots, n\} \]

while stopping criteria not met do

\[ x_{t+1} = \arg \max_{x} ECI(x|X_{1:t+1}, C_{1:t}) \]

\( \{c_1(x_{t+1}), \ldots, c_n(x_{t+1})\}, f(x_{t+1}) \} = \text{execute\_behavior}(x_{t+1}) \)

\( X_{1:t+1} = \{f(x_{t+1}), X_{1:t}\} \)

\( C_{1:t+1} = \{c_1(x_{t+1}), \ldots, c_n(x_{t+1})\}, C_{1:t} \} \)

Update GPs for the objective function/safety constraints

---

3 Crawling humanoid robot experiments

To evaluate our algorithm, we use a simulated iCub robot [13, 17] performing a crawling task. Learning how to crawl could prove especially useful in humanoid robot damage recovery, where attempting to walk again might constitute a big risk for further damages or be infeasible altogether (e.g. traversing a short or tight tunnel). Furthermore, solving this task serves as a stepping stone towards damage recovery for more advanced tasks (e.g. walking).

To generate a diversity of behaviors with MAP-Elites, we augment an initially 4D behavior descriptor, defined as the fraction of time each arm/leg spent on the ground, with a safety dimension that encodes the sum of contact point forces. sIT&E optimizes for crawling speed and is constrained by a safety threshold for the sum of contact point forces. This threshold is determined after conducting several preliminary experiments in order to understand the correlation between the robot’s behavior and the contact point forces at high crawling speeds. To optimize the acquisition function, we iterate over all

---

\(^3\)The reality gap refers to the differences between simulated and physical systems.
the points in the behavior-performance map (which contains approximately 1500 behaviors), and select a behavior that is estimated to be the most promising above the safety threshold.

We compare 3 algorithms in terms of the best safe performance observed and unsafe trials attempted: (1) IT&E maximizing crawling speed; (2) a multi-objective [8] IT&E algorithm (MO-IT&E; based on the Expected Hypervolume Improvement [10, 18]), that maximizes the crawling speed and minimizes the sum of contact point forces, therefore, building a Pareto front from which the safest behavior can be chosen; and (3) sIT&E maximizing crawling speed within the safe region as described above. We test 4 damage conditions: (1) locked shoulder joint, (2) locked hip joint, (3) locked shoulder joint & angled elbow, and (4) combination of 2 & 3.

We compare 3 algorithms in terms of the best safe performance observed and unsafe trials attempted: (1) IT&E maximizing crawling speed; (2) a multi-objective [8] IT&E algorithm (MO-IT&E; based on the Expected Hypervolume Improvement [10, 18]), that maximizes the crawling speed and minimizes the sum of contact point forces, therefore, building a Pareto front from which the safest behavior can be chosen; and (3) sIT&E maximizing crawling speed within the safe region as described above. We test 4 damage conditions: (1) locked shoulder joint, (2) locked hip joint, (3) locked shoulder joint & angled elbow, and (4) combination of 2 & 3.

Figure 2: Comparison between IT&E, MO-IT&E and sIT&E. Each algorithm is ran 20 times for 4 different behavior-performance maps. We report the best safe performance (i.e., the fastest crawling speed within the safe region observed during the learning process) (upper row) and number of unsafe trials attempted (violating the constraints) (lower row). Horizontal black lines represent medians.

To avoid depending on a single behavior-performance map, we use 4 independently-generated maps and run each algorithm 20 times for 30 trials. We use the squared exponential kernel with \( \sigma = 0.1 \) and a GP noise value of 0.01. When using IT&E, the median number of dangerous trials is approximately equal to 29 (out of 30) in all damage settings (Fig. 2, lower row). For MO-IT&E, this number decreases, but it is still greater than 22. In contrast, sIT&E requires less than 10 unsafe trials for damages 1, 2, and 4, and 14 for damage 3. Pairwise comparisons indicate that the results are highly significant (\( p < 0.0001 \), Mann-Whitney U test). In terms of safe performance (crawling speed in m/s), sIT&E dominates over both IT&E and MO-IT&E in all damage settings (Fig. 2, upper row), with the results being statistically significant (\( p < 0.001 \)) in all cases apart from damage 3.

All experiments were conducted using the limbo framework [6]. A supplementary video is available at https://youtu.be/8earj-7WhsQ.

4 Conclusion

Our experiments show that the vanilla IT&E algorithm finds high-performing behaviors in a few trials, but most of the behaviors tested, including the best, final ones, are unsafe for the robot. Since the multi-objective approach searches for a set of Pareto-optimal trade-offs, it can find safe and high-performing behaviors; however, this approach still tests many unsafe behaviors during the learning phase. By contrast, the sIT&E algorithm finds gaits that are both safe and high-performing with only a handful of unsafe trials. Thanks to this property, we are confident that sIT&E is less likely to damage the real iCub than IT&E or BO. In future work, we will compare our results to approaches based on safety regions [2], which might be safer, but may prove too conservative performance-wise. Overall, this work shows that safety is a critical component for any robot learning algorithm and that constrained BO can provide a good basis to design algorithms that are both data-efficient and safe.
Acknowledgments

This work received funding from the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation program (grant agreement number 637972, project “ResiBots”).

References

[1] Christopher G. Atkeson et al. What happened at the DARPA robotics challenge, and why? submitted to the DRC Finals Special Issue of the Journal of Field Robotics, 2016.

[2] Felix Berkenkamp, Andreas Krause, and Angela P Schoellig. Bayesian optimization with safety constraints: safe and automatic parameter tuning in robotics. arXiv:1602.04450, 2016.

[3] Roberto Calandra, André Seyfarth, Jan Peters, and Marc Peter Deisenroth. An experimental comparison of Bayesian optimization for bipedal locomotion. In 2014 IEEE International Conference on Robotics and Automation (ICRA), pages 1951–1958. IEEE, 2014.

[4] Jennifer Carlson and Robin R. Murphy. How UGVs physically fail in the field. IEEE Transactions on Robotics, 21(3):423–437, 2005.

[5] Konstantinos Chatzilygeroudis, Vassilis Vassiliades, and Jean-Baptiste Mouret. Reset-free Trial-and-Error Learning for Data-Efficient Robot Damage Recovery. arXiv:1610.04213, 2016.

[6] Antoine Cully, Konstantinos Chatzilygeroudis, Federico Allocati, and Jean-Baptiste Mouret. Limbo: A fast and flexible library for bayesian optimization. arxiv:1611.07343, 2016.

[7] Antoine Cully, Jeff Clune, Danesh Tarapore, and Jean-Baptiste Mouret. Robots that can adapt like animals. Nature, 521(7553):503–507, 2015.

[8] Kalyanmoy Deb. Multi-objective optimization. In Search methodologies, pages 403–449. Springer, 2014.

[9] Jacob R Gardner, Matt J Kusner, Zhixiang Eddie Xu, Kilian Q Weinberger, and John Cunningham. Bayesian optimization with inequality constraints. In ICML, pages 937–945, 2014.

[10] Iris Hupkens, André Deutz, Kaifeng Yang, and Michael Emmerich. Faster exact algorithms for computing expected hypervolume improvement. In International Conference on Evolutionary Multi-Criterion Optimization, pages 65–79. Springer, 2015.

[11] Nick Jakobi, Phil Husbands, and Inman Harvey. Noise and the reality gap: The use of simulation in evolutionary robotics. In European Conference on Artificial Life, pages 704–720. Springer, 1995.

[12] Sylvain Koos, Jean-Baptiste Mouret, and Stéphane Doncieux. The transferability approach: Crossing the reality gap in evolutionary robotics. IEEE Transactions on Evolutionary Computation, 17(1):122–145, 2013.

[13] Giorgio Metta, Giulio Sandini, David Vernon, Lorenzo Natale, and Francesco Nori. The iCub humanoid robot: an open platform for research in embodied cognition. In Proceedings of the 8th workshop on performance metrics for intelligent systems, pages 50–56. ACM, 2008.

[14] Jean-Baptiste Mouret and Jeff Clune. Illuminating search spaces by mapping elites. arXiv:1504.04909, 2015.

[15] Guanjiao Ren, Weihai Chen, Sakyasingha Dasgupta, Christoph Kolodziejski, Florentin Wörgötter, and Poramate Manoonpong. Multiple chaotic central pattern generators with learning for legged locomotion and malfunction compensation. Information Sciences, 294:666–682, 2015.

[16] Bobak Shahriari, Kevin Swersky, Ziyu Wang, Ryan P Adams, and Nando de Freitas. Taking the human out of the loop: A review of Bayesian optimization. Proceedings of the IEEE, 104(1):148–175, 2016.

[17] Nikolaos G. Tsagarakis, Giorgio Metta, Giulio Sandini, David Vernon, Ricardo Beira, Francesco Becchi, Ludovic Righetti, Jose Santos-Victor, Auke Jan Ijspeert, Maria Chiara Carrozza, and Darwin G. Caldwell. iCub: the design and realization of an open humanoid platform for cognitive and neuroscience research. Advanced Robotics, 21(10):1151–1175, 2007.

[18] Kaifeng Yang, Daniel Gaida, Thomas Bäck, and Michael Emmerich. Expected hypervolume improvement algorithm for PID controller tuning and the multiobjective dynamical control of a biogas plant. In 2015 IEEE Congress on Evolutionary Computation (CEC), pages 1934–1942. IEEE, 2015.