Online Damage Recovery for Physical Robots with Hierarchical Quality-Diversity

MAXIME ALLARD and SIMÓN C. SMITH, Imperial College London, UK
KONSTANTINOS CHATZILYGEROUDIS, University of Patras, Greece
BRYAN LIM and ANTOINE CULLY, Imperial College London, UK

In real-world environments, robots need to be resilient to damages and robust to unforeseen scenarios. Quality-Diversity (QD) algorithms have been successfully used to make robots adapt to damages in seconds by leveraging a diverse set of learned skills. A high diversity of skills increases the chances of a robot to succeed at overcoming new situations since there are more potential alternatives to solve a new task. However, finding and storing a large behavioural diversity of multiple skills often leads to an increase in computational complexity. Furthermore, robot planning in a large skill space is an additional challenge that arises with an increased number of skills. Hierarchical structures can help to reduce this search and storage complexity by breaking down skills into primitive skills. In this article, we extend the analysis of the Hierarchical Trial and Error algorithm, which uses a hierarchical behavioural repertoire to learn diverse skills and leverages them to make the robot adapt quickly in the physical world. We show that the hierarchical decomposition of skills enables the robot to learn more complex behaviours while keeping the learning of the repertoire tractable. Experiments with a hexapod robot both in simulation and the physical world show that our method solves a maze navigation task with up to, respectively, 20% and 43% less actions than the best baselines while having 78% less complete failures.

CCS Concepts: • Computing methodologies → Evolutionary robotics; Lifelong machine learning; Robotic planning;

Additional Key Words and Phrases: Hierarchical learning, Quality-Diversity, robot learning

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1 INTRODUCTION

Robots can learn skills to solve various problems through methods coming from the field of robot learning [Akkaya et al. 2019; Cully et al. 2015; Miki et al. 2022]. Some of the learning methods include Deep Learning, Reinforcement Learning, and Quality-Diversity (QD) [Chatzilygeroudis

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Authors’ addresses: M. Allard, S. C. Smith, B. Lim, and A. Cully, Adaptive and Intelligent Robotics Lab, Imperial College London, Exhibition Rd, South Kensington, London, United Kingdom, SW7 2AZ; email: maxime.allard@imperial.ac.uk; K. Chatzilygeroudis, Computer Engineering and Informatics Department, University of Patras, University Campus, Patras, Greece, 26504.

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However, the deployment of robots in real-world scenarios is still a hard problem [Chatzilygeroudis et al. 2019]. One of the main problems that robots need to tackle while being deployed in the physical world is the occurrence of unforeseen situations (such as damages) that can greatly alter the performance of the robot. Other problems might include robustness to external perturbations, generalisation of experience in novel scenarios, and interaction with other complex agents (both artificial and natural) among several others [Thrun 2002].

It is impossible for people developing robots to predict all the scenarios a robot will end up in and this makes it very difficult to train the robot for all possible situations. The literature proposes different techniques to counter this problem. For example, we can train an agent on relevant and automatically generated scenarios [Fontaine and Nikolaidis 2020a; Gambi et al. 2019; Mullins et al. 2017; Rocklage et al. 2017] before the deployment or we can make the robot learn on how to adapt to unknown situations during deployment. Instead of relying on a single fixed control policy, a robot that adapts has the potential to perform efficiently in previously unseen scenarios [Åström and Wittenmark 2013]. Adaptive control has been proposed as a way of tuning parameters during exploitation [Åström and Wittenmark 2013; Cameron and Seborg 1983]. In autonomous robots, the parameters of the controller can be directly updated based on the error of a predictive model to maintain an exploratory behaviour [Minniti et al. 2022; Smith et al. 2020]. Another way to achieve adaptation is to leverage multiple diverse control policies. For example, methods that leverage QD [Chatzilygeroudis et al. 2021; Cully and Demiris 2018b; Pugh et al. 2016] algorithms have shown that the diversity of pre-computed solutions is a key factor for fast adaptation [Chatzilygeroudis et al. 2018; Cully et al. 2015; Kaushik et al. 2020].

Generating solutions beforehand requires a robot to have a lot of interactions with an environment. Having interactions with the physical world requires manual resets, hardware replacements, battery replacements (if no other power supply is provided), and so on. Consequently, the learning process is usually done in simulation since it requires less supervision and time than running physical trials with a robot. All of these restrictions are not present in simulation which makes the simulation a less time-consuming and less laborious way of getting thousand hours of experience with a robot. Simulators, albeit being easier to use than the real world, are imperfect representations of the physical world which means that a simulation-to-real-world gap will always be present for the learned solutions.

In the work of Cully et al. [2015], the authors present the Intelligent Trial and Error (ITE) algorithm which uses QD to find around 13,000 solutions for a hexapod robot to walk in different directions in simulation and then adapt to damages in seconds in the real world. The training is done in simulation since each solution requires 5 seconds of walking. The training of the solutions was done with 40 million evaluations which corresponds to $40 \times 10^6 \times 5 = 2 \times 10^8$ seconds, or 6.3 years of controller execution that would be necessary to train such a repertoire in the real world. In a real-world scenario where the robot has a damaged leg, ITE uses its large repertoire with a diverse set of controllers to find the solutions that are unaffected by the leg damage. The algorithm updates a set of Gaussian processes (GPs) [Rasmussen and Williams 2005] with experiences gathered by trial and error in the environment to find the best solution in the pre-trained repertoire. In ITE, the repertoire of solutions is used to solve a single skill. To accomplish a task such as navigation under damage, the algorithm requires more skills, e.g., turning left, turning right, moving backward, and so on. However, it is intractable to generate all the required solutions for each of the skills. Other approaches to repertoire-based adaptation with QD include the Reset-Free Trial and Error (RTE) algorithm [Chatzilygeroudis et al. 2018] and the Adaptive Prior Selection for Repertoire-Based Online Learning (APROL) algorithm [Kaushik et al. 2020]. RTE and APROL generate diverse controllers that are used for planning in order to solve navigation tasks with a damaged
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Fig. 1. Schematic representation of a three-layered hierarchical trial and error repertoire for omni-directional hexapod locomotion. The top \textit{behavioural repertoire (BR)} selects three different solutions from the middle level BR to make the robot move for 3 seconds ($3 \times 1$ second behaviours). The middle layer then fetches six leg controllers per behaviour ($3 \times 1 \times 6$ leg controllers in total) for the robot to achieve the desired upper-level behaviour. The middle layer has a depth (represented by a cylinder) from which the secondary behaviour can be chosen. Here, we visualise the different secondary behaviours as different layers in the middle layer to show that a single primary behaviour (top of the cylinder) can have multiple secondary behaviours (axis of the cylinder). In our case, each secondary behaviour consists of a different gait that does not use all the legs. We represent the legs that are not used during the gait with a red colour.

robot. APROL takes advantage of multiple trained repertoires with different prior knowledge on possible future conditions, e.g., damage or change in the friction between the robot and the ground, whereas RTE only uses a single repertoire.

All of the approaches above assume that a subset of the pre-trained solutions in a repertoire can be used effectively to achieve adaptation in the real world. The stochasticity of the environment and the complexity of the tasks may break this assumption if the diversity of solutions is not large enough. One approach to tackle this problem is to increase the number of solutions in the repertoire, but at the cost of sampling efficiency, memory storage, and a larger solution space. Increasing the number of stored solutions might increase the diversity but it will make it harder to select the correct skill. An increased solution space can impact the training procedure since it will make it more difficult to fully explore and optimise the space. Furthermore, any algorithm that needs to select the learned skills for downstream tasks (e.g., path planning algorithm) will have to chose among thousands of solutions which makes the task even more complex.

To tackle these issues, it is possible to increase the diversity of solutions for robot control by decomposing the search-space as a hierarchy and by efficiently organising controllers [Merel et al. 2019]. The different layers allow for compositionality and re-usability of solutions (i.e., controllers). Furthermore, the use of hierarchies can help with transferability to other domains and few-shot learning [Cully and Demiris 2018a; Eppe et al. 2020; Etcheverry et al. 2020]. In this work, we propose to combine the quality of finding diverse solutions coming from QD and the efficiency of hierarchical structures by learning hierarchical controllers to make robots adapt quicker to unforeseen scenarios.

To this end, we introduce an extended analysis of the \textit{Hierarchical Trial and Error (HTE)} algorithm [Allard et al. 2022], which uses \textit{hierarchical behavioural repertoires (HBRs)} [Cully and Demiris 2018a] (see Figure 1). HBRs are composed of layers with different repertoires of solutions. Each repertoire stores solutions that range from low-level motor commands to high-level task goals descriptions. In HBRs, the layers are connected by one or more edges, implemented as the genotype of each solution and each layer executes one or more behaviours from the layers.
below it. The different layers of HTE are trained to exhibit different behaviours on the robot (e.g.,
moving a single leg, walk for 1 second). Following RTE, our method uses the experience generated
by the robot during the deployment phase to update a set of GPs. The GPs are used in a planning
step with a Monte Carlo Tree Search (MCTS) algorithm to find the best action in the hierarchical
repertoire based on the current state of the robot and the goal of the task.

To test our hierarchical algorithm, we compare it first to RTE and APROL in a set of experiments
with a hexapod robot in a simulated maze environment before evaluating our approach in the real
world. For the real-world experiments, we build a similar maze to the one in simulation and remove
a leg from the hexapod robot to test how well we can adapt in real conditions. Additionally, the
robot is never trained with damage nor was it trained in the physical world. Finally, our extended
analysis tries to answer the following questions around the usefulness of HTE:

– Is it possible to find diverse and useful controllers for omni-directional hexapod locomotion
  with HTE in the real world?
– Can we increase the diversity of learnt skills by using an additional secondary behavioural
descriptor in the hierarchy?
– Can HTE solve complex downstream robot tasks both in simulation and in the physical
  world?
– Is HTE able to adapt to damages in real-world experiments?
– Can we leverage the diversity of skills while keeping the execution time of HTE tractable?

Our results show that HTE can find diverse solutions by decomposing the search space hierar-
chically. This makes the optimisation process simpler in comparison to finding solutions in the full
extended solution space. In comparison to the baselines, HTE requires less steps to solve the task
and less failures in a maze navigation task (i.e., downstream task) since it can effectively leverage
the large collection of hierarchical skills.

This work extends the original "Hierarchical Quality-Diversity for Online Damage Recov-
ery” [Allard et al. 2022] paper in three aspects. First, we show that the Trial and Error process
for the selection of secondary behaviours, compared to a random selection, helps the hexapod ro-
bot to adapt faster in the case of damages. Second, we explore the capacity of the algorithm to
perform well in the physical world by running experiments with a real robot. The HTE algorithm
is able to adapt quicker to damages in the real-world in comparison to the baselines. This result is
specially relevant as adaptation is harder in the physical world than in simulation. Furthermore,
solutions learned in simulation might not translate directly to the physical world. This gap is reduced
by the adaptation and online optimisation mechanisms of the algorithm. Lastly, the hierarchical
architecture reduces the adaptation time. To showcase the reduction in adaptation time, we com-
pare different algorithms in the physical world and record their time to complete the maze task
(see Figure 2(a)).

2 BACKGROUND AND RELATED WORK

Quality-Diversity. QD has shown to be a powerful optimisation tool that can solve complex
problems such as robot damage recovery fast and reliably [Cully et al. 2015], achieving state-of-
the-art results on unsolved Reinforcement Learning tasks in sparse-reward environments [Ecof-
fet et al. 2021], human–robot interaction [Fontaine and Nikolaidis 2020a], robotics [Eysenbach
et al. 2019; Grillotti and Cully 2022; Mouret and Maguire 2020; Nordmoen et al. 2021; Salehi et al.
2021], games [Perez-Liebana et al. 2021; Sarkar and Cooper 2021; Steckel and Schrum 2021], or
constrained optimisation [Fioravanzo and Iacca 2021] among several others.

QD algorithms [Chatzilygeroudis et al. 2021; Cully and Demiris 2018b; Pugh et al. 2016] are
a family of evolutionary algorithms that aim to generate a collection of diverse and locally
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The diversity of solutions is obtained by defining a *behavioural descriptor* $b$ (also known as feature vector) used to characterise a solution. This diversity of solutions contrasts with classical optimisation algorithms that only look for the highest performing solution. For example, a mobile agent can reach a final destination by following different (diverse) paths. Each one of these paths is a valid solution to reach the target but they are all defined different trajectories to reach the destination. In QD algorithms, the expert defines the $n$–dimensional *behavioural space* as $B \in \mathbb{R}^n$. After evaluation, each solution $\theta$ is associated with a behavioural descriptor $b_\theta$ that defines their behaviour in the space $B$. Usually, the engineer defines the behavioural descriptor $b_\theta$ manually, which requires expert knowledge and can result in a solution bias during the evolutionary process. To define the behavioural descriptor automatically, recent methods encode the behaviours into a latent space with dimensionality-reduction algorithms [Cully 2019; Cully and Demiris 2018a; Grillotti and Cully 2022; Laversanne-Finot et al. 2018; Paolo et al. 2020] to discover behaviours in the latent space.

The solutions $\theta$ are defined by a genotype $g$, which belongs to the $k$-dimensional *genotype space* $G \in \mathbb{R}^k$. The most popular QD algorithms include MAP-Elites [Mouret and Clune 2015] and Novelty Search [Lehman and Stanley 2011]. We use MAP-Elites in our method to generate the repertoires. In MAP-Elites, once a solution has been evaluated, it is stored in a grid-like archive, called repertoire. The repertoire discretises the *behavioural space* $B$ to store individuals in distinct cells. In the case that two solutions have the same behavioural descriptor, the algorithm keeps the one with the highest fitness in the repertoire and discards the other.

**Hierarchical Organisation of Autonomous Control.** In nature, the nervous system of complex organisms, e.g., mammals, uses hierarchical controllers for robust and versatile behaviours [Merel et al. 2019]. Even more, authors in cognitive psychology have deemed hierarchies as critical mechanisms for developing intelligent agents [Eppe et al. 2020].

Hierarchical structures allow algorithms to compose complex solutions out of primitive ones, which helps with the optimisation process. For example, hierarchies are used to stack different levels of abstracted goals to solve high-dimensional problems in Reinforcement Learning [Gehring et al. 2021; Nachum et al. 2018] or to enable hierarchical latent spaces to discover a diversity of behavioural representations in evolutionary algorithms [Etcheverry et al. 2020].

Furthermore, Hierarchical Genetic Algorithms [Ryan et al. 2020] use hierarchies with fitness functions of different granularities per layer, allowing the evolution of both coarse and fine behaviours at different levels. Also, hierarchical abstractions are effective at controlling robots in more complex environments. Several works show that the hierarchical abstraction of behaviours allows robots to solve complex tasks [Duarte et al. 2016; Jain et al. 2021; Li et al. 2021]. In these works, a neural network uses planning to choose the actions from a repertoire of primitive behaviours.
QD has been successfully combined with hierarchical structures for a rapid divergent search of solutions with trees [Smith et al. 2016] or to create HBRs that can be transferred across different types of robots to solve complex tasks such as drawing digits with a robotic arm [Cully and Demiris 2018]. Our method is inspired by this latter work on HBRs and reuses the concept to create a diverse set of solutions.

**QD-Based Adaptation.** Adaptability is a key feature for controlling robots in realistic scenarios. Usually, real-world scenarios define intractable state and solution spaces. It is impossible for a robot to have a pre-defined solution for each possible situation. Thus, the robot has to adapt to any occurring situation in real-time.

Cully et al. introduced the ITE algorithm as an adaptive control method based on MAP-Elites and GPs for planning and adaptation [Cully et al. 2015]. The most significant results of ITE include the rapid adaptation of a hexapod robot with damaged legs. Some other works build upon ITE to introduce a local adaptation mechanism to improve the simulation-to-reality transfer [Kim et al. 2021], to optimise a swarm of robots [Bossens and Tarapore 2021], or to find new game levels with different difficulties [Duque et al. 2020]. Along the same lines, Chatzilygeroudis et al. introduced the RTE algorithm [Chatzilygeroudis et al. 2018]. In this algorithm, a robot is able to adapt to unseen scenarios, e.g., damage in a leg, while executing a navigation task. The algorithm uses a repertoire of solutions and GPs to quickly find well performing solutions for this task. We base our work on this method and introduce further details in the next section. Similarly, the APROL algorithm [Kaushik et al. 2020] adapts the behaviour of a hexapod to different damages while executing a navigation task. To do so, the algorithm chooses the best skill, using GPs, among a set of dozens of repertoires of solutions that have been trained on potential scenarios (e.g., damage to the legs or different friction coefficients) that the robot could face during deployment. In an iterative process, APROL selects the best solutions from the repertoire that is the most likely to represent the actual conditions (i.e., friction coefficient or leg damage). These methods show that the solutions created by QD are useful to adapt to different situations while executing a task. Similarly, the HTE algorithm is built upon the idea to create a diverse set of solutions with an HBR first and subsequently find the best skill for a situation with Bayesian Optimisation.

### 3 PRELIMINARIES AND MOTIVATION

#### 3.1 Reset-Free Trial and Error

The RTE algorithm [Chatzilygeroudis et al. 2018] is a powerful method to enable a robot to adapt to changing environments or scenarios in real time. First, a repertoire of solutions is created by MAP-Elites in simulation where each solution is stored with respect to the observed behavioural descriptor $b_\theta$. After creating the repertoire in simulation, it is used as a prior for the mean of a set of GPs. The main loop of RTE consists of running a MCTS [Coulom 2007] algorithm to plan the next best action $b_{t+1}$ together with the GPs given the actual state of the robot $s_t$. Since the simulation environment is always imperfect, GPs map the behavioural descriptors $b_\theta$ to observed behaviours $b_{\text{observed}}$ in the new environment. Once the action from the repertoire is executed, the observed behavioural descriptors are used to update the Gaussian process before RTE does the next round of planning. Finally, this main loop of RTE runs until a stop criterion is met, e.g., reaching the goal state.

RTE has been successfully used to enable a hexapod robot and a velocity-controlled differential drive robot to reach its final destination even with one or more damages. The algorithm takes advantage of the diversity of skills created by the MAP-Elites algorithm and shows to be very effective at finding solutions in the repertoire of diverse solutions that are suitable for different situations. In contrast to ITE, RTE has more diverse skills but only one way to execute them.

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behaviour implies that in an unexpected situation the algorithm needs to have a viable solution in the repertoire for each skill which is not always the case. For this reason, an effective algorithm relies on a good diversity of skills with a redundancy of ways to execute these skills. On one hand, ITE promotes the diversity of executing a single skill, and on the other hand, RTE pushes for a diversity of skills without a diverse way of executing them. Our method aims to optimise for both properties to make the adaptation of robots more effective.

3.2 Hierarchical Behavioural Repertoires

To increase the number of ways to achieve different skills, HTE extends the HBR algorithm [Cully and Demiris 2018a] to learn locomotion skills for robots. HBR algorithms are effective at finding complex skills that can be used across different robots (e.g., drawing digits with a robot-arm and a humanoid robot [Cully and Demiris 2018a]) without retraining all the layers. Structurally, HBRs consist of layers of MAP-Elites repertoires which are chained together to create diverse skills. A bottom layer could consist of a controller that makes a robotic arm move to any reachable point in a defined space. Following this architecture, we can train a second layer that draws a line from one point to another by reusing solutions from the first layer (i.e., reach two points with the arm). These new skills can be used by a third layer to create arcs with five different lines. Finally, the robotic arm can learn how to draw digits by drawing different arcs with the skills from the third layer. All the layers are trained sequentially (i.e., one after the other) from the bottom up since each repertoire of behaviours (i.e., layer) is using previous BRs to create more complex skills. In the special case of only using one layer, the HBR algorithm reduces to a classical QD algorithm with a single repertoire. HBR algorithms are able to create complex solutions (e.g., draw digits with a robotic arm) by building on top of previously built repertoires. HTE uses the HBR algorithm to optimise its skills in different subspaces (i.e., different BRs) of the full solution-space to find the complex skills which the robot requires for adaptation during the deployment.

Behavioural Descriptor and Genotype. Each layer $k$ in HTE contains solutions $\theta_k$ with a behavioural descriptor $b_k$. The solutions are defined by their genotype $g_k$ where $g \in G$. In the following section, $k = 1$ is the lowest layer which directly interfaces with the robot whereas $k = 2, \ldots, K$ are subsequent layers for a $K$-layered HBR. Since multiple layers are stacked on top of each other, each repertoire needs to be connected to the others. In HBRs, this is done by using a genotype $g_k$ definition that maps to the behavioural space of the other layers.

Stacking. The solutions $\theta_1$ in the lowest layer correspond to the parameters we use to directly control a robot. For the other layers, the solutions $\theta_k$ in layer $k$ use the behavioural descriptor space of the lower layers as the action space. In practice, this is implemented as a succession of behavioural descriptor coordinates $b_{k-1}$ which is defined in the genotype $g_k$ of a solution. This definition allows to produce a successive execution of the corresponding controllers in the lower layers $k - 1$. In other terms, the middle layer is a mapping $\phi() : B_2 \rightarrow B_1$ from the behavioural descriptor space of the middle layer to an output space, which corresponds to the behavioural descriptor space of the lower layer.

Hierarchical repertoires are not limited by the number of layers and can create increasingly complex solutions by simply stacking more layers of repertoires.

4 HIERARCHICAL TRIAL AND ERROR

4.1 Hierarchical Architecture

Our HTE algorithm leverages the hierarchical repertoires to improve the diversity of skills, decompose complex solution spaces, and make the adaptation to different damage scenarios more
effective. In this implementation, the HTE algorithm uses a three-layered HBR (see Figure 1) where (i) the bottom layer defines the movement for a single leg for 1 second, (ii) the middle layer makes the robot walk for 1 second by selecting six controllers for the legs, and (iii) the top layer makes the robot walk for 3 seconds by chaining three controllers from the middle layer. Even though our implementation has three layers, HTE can be used with an arbitrary number of layers in the HBRs, and it can be naturally applied to different tasks/robots.

**The HTE Architecture.** With the HTE algorithm, our goal is to find behaviours that control the robot in various directions while doing it in many different ways. To this end, we present a hierarchical structure that consists of three layers, namely: a "Bottom Layer" directly controlling the joints of a single leg of the hexapod, a "Middle Layer" controlling the robot’s displacement for a second, and the "Top Layer" which learns how to make the robot move to a specific x, y position after 3 seconds. The **bottom** layer directly controls the legs of the hexapod. A solution in the repertoire is an open-loop controller for one single leg. Each leg of the hexapod has three motors, where the motor attached to the body uses a periodic function \( \varphi_1(t, a, p, d) \) at each timestep \( t \) with parameters \( a \) for the amplitude, \( p \) for the phase shift, and \( d \) for the duty-cycle (see [Cully et al. 2015] for more information on the duty-cycle and the periodic function). The two other motors use the same periodic function \( \varphi_2(t, a, p, d) \) such that the legs are always perpendicular to the bottom.

We use \( a_1, p_1, d_1 \) to control the first motor and \( a_2, p_2, d_2 \) to control the second and third motors. This configuration means that the **genotype** consists of six parameters, namely, \( g_1 = \{a_1, p_1, d_1, a_2, p_2, d_2\} \). The **behavioural descriptor** \( b_1 \) for the bottom layer is measured at the end of a simulation of 1 second for each leg. The descriptor is defined as the height \( h \) of the move, the swing distance \( d_{swing} \) and the duty cycle \( d \) of the second and third motor. The duty-cycle \( d \) in this case is both a parameter and a **behavioural descriptor**. To encourage minimal energy consumption, the **fitness function** is set as the sum of the commands that are sent to the motors throughout the simulation.

For the **middle** layer, the **genotype** consists of selecting six leg behaviours from the bottom layer \( g_2 = \{b_1, b_2, \ldots, b_6\} \) where \( b_l \) is a behavioural descriptor vector for solutions of the bottom layer from a specific leg where \( l \in \{1, 2, 3, 4, 5, 6\} \). The **behavioural descriptor** has three dimensions and consists of the \( x, y \), and \( \text{yaw} \) displacement of the robot after 1 second. The **fitness function** measures the angular distance between the robot’s final orientation and an ideal circular trajectory (similar to existing works [Cully and Mouret 2013]). The resulting repertoire consists of controllers that enable the robot to walk in any direction for 1 second.

Lastly, in the **top** layer, the **genotype** consists of three behavioural descriptors from the middle layer, \( g_3 = \{b_1, \ldots, b_3\} \) which make the robot move for 1 second each. The **behavioural descriptor** of this top layer is the final \( x, y \) position (i.e., \( x, y \) displacement, similar to Cully and Mouret [Cully and Mouret 2013]) of the robot which is measured after 3 seconds of simulation. Our **fitness function** is similar to the middle layer namely the angular distance between a perfect trajectory and the robot’s orientation.

**Primary and Secondary Behavioural Descriptors.** To find a larger diversity of solutions in QD algorithms, we could make the behavioural space \( B \) larger by adding additional dimensions to it. However, this can quickly lead to an exponential growth of the number of stored solutions in the repertoire which will make it (i) challenging to cover the behavioural space due to the decrease of evolutionary selection pressure that happens with large collections [Cully and Demiris 2018b] and (ii) difficult to store it in memory even on modern computers. In hierarchical repertoires, if the dimensionality of the behavioural space \( B \) on lower levels increases, we can achieve more combinations for the high-level skills (and thus increase the diversity). The difference between both approaches is that lower layers in hierarchical repertoires can store fewer and simpler solutions...
to cover an equivalent behavioural space than a traditional single-layered, or “flat”, repertoire. To be more descriptive, we can take the example of robot locomotion. Let us assume a robot can walk to many different positions in 3 seconds, then we would have to store all the solutions that could get us to different positions (i.e., $x$, $y$ displacement is our behavioural descriptor) if we are using a single-layered repertoire. However, in a hierarchical setting, we can store solutions that get us to different positions in 1 second (i.e., a much smaller behavioural space) and then combine these solutions to get 3 second locomotion skills. The combination of skills does not require any additional storing of solutions and is thus more efficient. This means that the growth in size is significantly lower than it is for complex solutions that are trained in a traditional repertoire.

In HBRs, to distribute different information flows to different subsystems in the hierarchy (i.e., information factorisation [Merel et al. 2019]) we can increase the size of our behavioural space $B$ in the middle layer of the HBR by increasing $B$ with additional secondary behavioural descriptor $b_{sec}$ dimensions. The dimensions of the behavioural descriptor which were originally described in the previous section are called primary dimensions and they remain unchanged. The additional dimensions of our behavioural space are secondary which means that higher level layers do not have to define these as part of their genotype when selecting solutions from the lower repertoire. The secondary dimensions can be used to execute solutions with the same primary behavioural descriptors but in different ways. It is important to note that secondary behavioural dimensions are not used during the training of the higher-level layers but only used to keep a diversity of skills that can be used during the adaptation phase. If we would simply add these dimensions to the middle layer during the training process, we would increase the search space for the higher levels which is something we want to avoid. Adding the dimensions to the top level layer would result in a very large behavioural space which, in turn, decreases evolutionary pressure as mentioned in the previous paragraph.

The training of the upper layers remains unchanged by directly selecting the solution in the lower layer with the nearest primary behavioural descriptor from the genotype value, without considering the secondary descriptor. Doing so, reduces the search space for the top level and helps the optimisation process to find diverse skills.

In our implementation of HTE for the hexapod, we extend our middle layer with six additional dimensions for the secondary descriptors. In addition to the three existing primary dimensions $b_{prim}$, we now have the secondary behavioural descriptor values $b_{sec}$ which measure the ground contact for each leg (1 if it is in contact with the ground for more than 30% of the time, otherwise 0). Since we have 6 legs, this gives us 6 additional secondary dimensions with 64 different possibilities (see Figure 1). The top layer will keep the same genotype as it focuses only on primary behavioural descriptors during the training. The secondary descriptors will be used by HTE during the adaptation phase to select the most appropriate way to execute each skill given the condition of the robot.

### 4.2 Online Hierarchical Skill Adaptation

We are interested in leveraging the diversity that we have incorporated into the hierarchical architecture to adapt the behaviour of the robot to different situations in the context of a maze navigation task. The adaptation is done by selecting skills that are able to recover their behaviour for a specific situation (e.g., damages).

**Primary Behaviour Selection via RTE.** HTE combines the adaptation and planning capabilities of RTE with the skill expressivity of the HBR. To this end, RTE uses the HBR in HTE like a traditional single-layered repertoire by exclusively interacting with the top layer. RTE chooses which skill should be executed from the repertoire to come closer to the next goal by using
Fig. 3. Trial and error selection of secondary behavioural descriptors. First, we select a secondary descriptor (purple leg) and a primary descriptor (x and y displacement) and execute it. Note that here we use purple to visualise the secondary behaviour that we want to try and red to show which leg is physically damaged. Second, we observe the error of behaviour on the damaged robot (red leg), and lastly we update the GPs to find secondary descriptors that match the observed behaviour.

MCTSs and GPs. Since HTE can execute each high-level skill with different secondary behavioural descriptors, we do not only need to choose which high-level skill to execute with RTE but we also need to select a secondary behavioural descriptor to adapt to the situation.

**Secondary Behaviour Selection via Trial and Error.** To find the optimal secondary descriptor and adapt to an unforeseen situation, HTE minimises the error $\varepsilon$ between the observed primary behavioural descriptor and the desired one. We define $\varepsilon$ as

$$\delta = |b' - b_\theta|,$$

$$\varepsilon = \exp \left( -k \frac{\delta}{2|b_\theta| - c} \right),$$

where $\delta$ is the error between the observed primary behavioural descriptor $b'$ and desired primary behavioural descriptor $b_\theta$. Both $b'$ and $b_\theta$ are the behavioural descriptor vectors with the $x, y$ coordinates of the robot’s centre of mass and the desired yaw rotation ($b = \{x, y, yaw\}$) (see Section 4.1), and $k, c$ are positive hyper-parameters to scale and shift the data, respectively. In our setting, we used $c = 0.5$ and $k = 4$. This error measure is inspired from the error measure introduced by APROL [Kaushik et al. 2020].

To minimise the error $\varepsilon$ (Equation (2)), we use Bayesian Optimisation with GPs [Rasmussen and Williams 2005]. GPs are a family of stochastic processes that are particularly attractive for this kind of regression problems because of their data-efficiency and uncertainty quantification. The GPs will learn to predict the error $\delta$ that a desired primary behaviour will have at every step for all combinations of a high-level skill and

Fig. 4. Maze navigation task. The damaged (left middle leg) hexapod robot needs to reach the purple circle in a least amount of steps.
Table 1. QD Parameters Used for HTE with a Population of 200 Individuals

|                     | Top Layer             | Middle Layer           | Lower Layer                        |
|---------------------|-----------------------|------------------------|------------------------------------|
| **Behaviour**       | 3-Second X, Y         | 1-Second X, Y, Yaw     | Height and stance of a single leg swing |
| **Behaviour Descriptor** | b = {x, y}        | b = {x, y, yaw}        | b = {h, d_{swing}, d}               |
| **Genotype**        | g = {b_1, b_2, b_3}   | g = {b_1, b_2, ..., b_6} | g_1 = {a_1, p_1, d_1, a_2, p_2, d_2} |
| **Genotype Size**   | 9                     | 18                     | 6                                   |
| **Discretisation**  | 100 × 100 Grid        | 0.05 l-value           | 0.01 l-value                        |
| **Mutation Rate**   | 0.14                  | 0.11                   | 0.17                                |
| **Generations**     | 20000                 | 30000                  | 5001                               |
| **Fitness Function**| |                        | $\sum_{l=1:3} |m_l|$                 |

The mutation is polynomial with $\eta_m$ and $\eta_c$ both at 10.0. The discretisation of the behavioural space is defined by a grid (Top Layer) or an l-value. The l-value is the minimal euclidean distance between two behavioural descriptors that defines whether two individuals are diverse or are considered to have the same behaviour (i.e., are in the same cell). The angle $\Omega$ in the fitness function is defined as the difference between the angle of the tangent for a perfect circular trajectory $\omega$ and the orientation of the robot $\alpha$: $\Omega = \omega - \alpha$. For the Lower Layer, the fitness function is the sum of all the motor actuations we sent to a single leg, which we define as $m_l$, to minimize the energy.

The UCB method will pick the secondary descriptors that minimise the error $\epsilon$ given the current situation of the robot. This process is done during the deployment of the robot in the new situation without any resets (see Figure 3). At each iteration of the trial and error iteration in HTE, the GPs are updated with the new observed behaviours to refine their predictions of the least affected secondary descriptors. In HTE, we have a finite set of possible secondary behaviours and thus we can iterate over them to find the best high-level skill with RTE and the best secondary behavioural descriptor for a situation with UCB. Note that adaptation is not only useful for any unforeseen situation (e.g., damage) but it can improve the simulation-to-real-world transfer of skills which is important in robotics.

5 EXPERIMENTAL EVALUATIONS IN SIMULATION

5.1 Experimental Setup

We evaluate the benefits of HTE (with parameters in Table 1) in a maze solving task (see Figure 4) with the hexapod being damaged in several ways. We create seven different scenarios where a different damage is present within each: six scenarios where one of the legs is blocked in the air (different leg for each scenario) as shown in Figure 5 and one scenario where the two middle legs are damaged at the same time.

In the following experiments, we consider three baselines, namely RTE with a 2-dimensional repertoire (2D-RTE) [Chatzilygeroudis et al. 2018], RTE with a 8-dimensional repertoire (8D-RTE), and APROL [Kaushik et al. 2020]. The “flat” repertoires we use for RTE should have the same solution space (and same behavioural space) as the HBR used in HTE. The open-loop controllers for the flat repertoires are defined by a genotype with 36 parameters and they are executed for 3 seconds. For this purpose, the flat 8-dimensional repertoire version will have a behavioural descriptor space of $2 + 6$ dimensions where each controller is executed for 3 seconds. The first two dimensions correspond to the final x, y displacement of the robot, while the other six are the yaw and height and stance of a single leg swing.
Fig. 6. The left image represents the repertoire that belongs to the HTE method, and the right image corresponds to the 8-dimensional flat variant. Both show the $x$ and $y$ location after 3 seconds of movements for the robot on a flat plane. The right repertoire has a higher density since we collapse 8 dimensions onto 2 to compare them. The legend shows the fitness of the solutions (i.e., robot’s orientation).

the other six dimensions represent a binary leg contact similarly to the middle layer of HTE. For the 2-dimensional version, we use the final $x$, $y$ displacement as behavioural descriptor which is the same we use for the top layer of HTE (see Figure 6).

For the baselines, we use the code from the original authors of RTE, and we re-implemented APROL in C++ with the SferesV2 framework [Mouret and Doncieux 2010]. As planning method within APROL, we use MCTS and $A^*$ similarly to RTE which differs from the original implementation where only $A^*$ was used.

For APROL, we created 21 different flat 2-dimensional repertoires where each repertoire has been trained with a single or double leg damage on a flat terrain. For the flat repertoires used in RTE and APROL, we use the same hyper-parameters than in the original RTE paper.

For the simulations, we use the framework RobotDART\(^1\) which is an accessible C++ wrapper that allows to create robot tasks in the DART [Lee et al. 2018] simulator. The implementations for HTE and the experiments are made available online.\(^2\)

5.2 Can the Hierarchical Repertoire be More Diverse Than a Regular Flat Repertoire?

To compare the different repertoires, we created four repertoires for each variant and replicated the evaluations 30 times for each damage.

We want to compare the diversity of solutions produced by HBR, compared to the one produced by the 8D repertoire. We present the results in Table 2, where we observe that the flat version is able to find a high number of solutions. This result is expected since we have 640000 cells that can be filled. However, when projecting the content of the repertoire on the first two dimensions, namely the $x$, $y$ displacement, we can observe in Figure 6 that HTE covers a larger space (effective size) than the flat 8D repertoire. We report the coverage of this projection in Table 2 as the Effective Size which represents the number of cells that we have filled. In these comparisons, HTE has a better “effective” coverage and a better average fitness than the flat 8D repertoire. This demonstrates

\(^{1}\)https://github.com/resibots/robot_dart.
\(^{2}\)https://github.com/adaptive-intelligent-robotics/HTE.
Table 2. Results for Each Architecture (at $4 \times 10^6$ Evaluations)

| Algorithm | Repertoire Size         | Effective Size       | Mean Fitness       |
|-----------|-------------------------|----------------------|--------------------|
| HTE       | $2980.8 \pm 131.0$      | $2980.8 \pm 131.0$   | $-0.01 \pm 0.02$  |
| Flat-8D   | $72528.0 \pm 2809.4$    | $2531.5 \pm 111.8$   | $-0.21 \pm 0.02$  |

The numbers of solutions in the repertoire differ by one order of magnitude since the flat repertoire has 8 dimensions and the HBR version has only 2. The Effective Size is the number of cells we fill when projected on the first two dimensions and the Mean Fitness is the mean fitness of these individuals.

![Diagram](image)

(a) Final forward and lateral displacements ($x$, $y$ position) the hexapod robot can reach while using different secondary behavioural descriptors. The colour and size of the markers represent the number of secondary behaviours from the middle layer that we can execute without changing the behavioural descriptor of the solution in the top-layer repertoire.

(b) Each subplot shows the final $x$, $y$ positions we can reach with the hexapod while using different leg duties (i.e., more or less than 30% contact with the ground). On this plot we have one subplot per desired secondary behavioural descriptor where each leg is red if it is not used for that subplot.

**Fig. 7. Diversity created with secondary behaviours.**

that HTE can generate a better repertoire for the $x$, $y$ displacements which are the skills we are interested in for the navigation tasks.

### 5.3 Can We Modulate High-Level Skills with Secondary Behavioural Descriptors?

To test whether we can modulate high-level skills, we re-evaluate all solutions from the top-layer of HTE with the objective to reach the same behaviour descriptor (i.e., $x$ and $y$ position) while using different secondary behavioural descriptors in the middle-layer. For testing purposes, we use the same secondary behavioural descriptor for the full duration of the skill (i.e., the secondary behaviour will be the same for the three steps) which leaves us with 64 (two choices per leg which gives us $2^6$ possible combinations) possible choices for each high-level skill. Some of these secondary behaviours are expected to be impossible to achieve for the robot (e.g., not to use any of its legs). After re-evaluating the solutions, we count how many times the robot (i) exhibited the wanted secondary behaviour and (ii) whether the robot was able to reproduce its behaviour descriptor by reaching its original final $x$, $y$ position.

In Figure 7(a), we plot how many times the robot reaches the desired $x$, $y$ location after 3 seconds while executing different secondary behavioural descriptors. The size of the markers is proportional to the numbers of high-level skills that can be executed with secondary descriptors. On Figure 7(a), we have a big region in the centre with a large numbers of valid secondary descriptors.
Therefore, the robot is able to move to various \( x, y \) positions while using its legs differently to get there. We can observe that the number of secondary behaviours decreases near the edges of the repertoire. This inverse correlation can be expected as it is likely more challenging for the robot to find a large number of different ways to walk fast in different directions.

In Figure 7(b), each subplot corresponds to the final \( x, y \) positions reachable with a specific secondary behavioural descriptor (64 in total). This result shows which secondary descriptors are actually not feasible (e.g., the first column or first row of the subplots). On both figures, we can observe that HTE is able to use secondary behavioural descriptors to modulate its high-level skills when moving to the same final point. This shows that HTE can exhibit a different behaviour even though we have not expanded the behavioural space on the top layer during training. These results show that HTE successfully reuses the diversity within the hierarchical structure.

5.4 What are the Benefits of HTE on the Robot’s Adaptation Capabilities?

Finally, we evaluate the benefits of HTE and the additional behavioural diversity provided by the secondary behavioural descriptors on the robot’s adaptation capabilities. More specifically, we test the algorithm in a maze navigation task with a damaged hexapod (see Figure 4).

We run HTE in two different scenarios. First, an upper-baseline scenario where the damage of the robot is known and we can directly select a preferred secondary behaviour (called Perfect HTE). Second, a scenario where we let the robot adapt automatically by choosing the optimal secondary behaviours for the given situation with Bayesian Optimisation (see Section 4.2). We are interested in knowing which version is the most adaptive across different scenarios. Thus, we report the distribution of the median numbers of actions that a single variant replications needs across the seven tasks. Since we did 30 replications per repertoire we obtained \( 7 \times 30 = 210 \) median values for our report per variant. Moreover, we are interested in how the variants perform in the best-case and worst cases which is why we also report the 25th and 75th percentiles in addition to the medians.

From the results in Figure 8, we can see that the best performing algorithm is HTE with prior knowledge. The manual selection of the secondary descriptor based on the prior knowledge of the damage helps the robot to adapt since it will only use moves that do not use the damaged leg. However, we expect that this prior knowledge and expertise might not always be available. When this information is not available, HTE still performs better than all the other variants, even if it has to infer from experience the optimal secondary behaviours for recovery.

In median, we can observe across the replications that HTE needs 24 actions, while 2D-RTE needs 28, 8D-RTE 32, and finally APROL 39 actions. This result shows a 14.2% improvement for HTE over the best baseline, namely 2D-RTE for the median cases. We can see from the results in Figure 8 that RTE with a 2D repertoire performs better than the other baselines in the 25th percentile range. For example, for the 25th percentile, the robot only needs 22 actions in median to solve the seven tasks for the 2D-RTE variant and 19 for the HTE variant. APROL has the worst performance in the experiments which might be due to a reduced number of available repertoires (we use 21 repertoires instead of 57 repertoires in the original paper as we do not study the effect of friction). Another difference is that we use MCTS as a planner instead of A* from the original APROL study. For APROL, we see that even in the best scenarios we need 34 actions and for 8D-RTE we need 26.

HTE performs well even in the worst case scenarios (i.e., the 75th percentiles) where it takes 32 actions in median to solve the tasks in comparison to 40 for the 2D-RTE, 39 for 8D-RTE and 48 for APROL. In these worst case scenarios, we show a 20% improvement over the best baseline (2D-RTE). However, HTE still fails to match the performance of the Perfect HTE variant which only needs 16 actions for the 25th percentile, 19 for the median, and 24 for the 75th percentile of replications. Perfect HTE shows that there is still room for the design of a better secondary
Fig. 8. Box-Plot for the different variants of algorithms for which we report the 25, 50, and 75 percentile values for each replication. HTE is outperforming the baselines in each case showing that the hierarchy is helping with the adaptation to damages.

Fig. 9. Percentage of the experiments that failed to finish in under 80 actions for each variant.

behaviour selection in future work. The results on the downstream task for each algorithm are statistically different according to a Wilcoxon–Mann–Whitney test and a p-value < 1e-6 with a Bonferroni correction.

In a few cases, the robot may flip on its back and get stuck or stall in a corner of the maze. For these reasons, we limit the number of possible actions the robot can take to solve the navigation task to 80 (i.e., a failure). While this hard-coded value could bias the average of the results, the reported box-plots for the median values are less influenced by outliers. For the 25th and 75th percentile values, we do not use an interpolation for the same reasons, but we take the closest data point that corresponds to the \( n \)th-percentile value. In Figure 9, we show the failures across replications of each variant for the task. HTE has 78% less failures in the maze experiments when
compared to the best performing baseline in the maze (2D-RTE). 8D-RTE and APROL have less failures at the expenses of more steps. HTE is able to both solve the maze quickly while being more stable with regard to total failures.

The results show that the diversity created by HTE helps to improve the damage recovery capabilities of a hexapod robot in our maze experiment where the robot requires to find many diverse ways of executing a behaviour and navigate the maze.

5.5 Is the Trial and Error Method Selecting Useful Secondary Behaviours?

HTE is effective at adapting to damages because of the added diversity through secondary behaviours in the middle layer. To evaluate the effect of the trial and error approach within HTE, we ran HTE with a random selection of secondary behaviours at every step. Random selection will not reduce the diversity of executed skills but it will show whether selecting secondary behaviours has an effect on the results. The results from Figure 8 suggest that choosing the right secondary behaviour in the perfect HTE method enables our robot to solve the maze quicker than other approaches which is why we would like to get as close as possible to this perfect scenario. Figure 10 shows the distribution of mean actions HTE needs to solve the maze by using a random selection process in comparison to the trial and error approach described in Section 4.2. The trial and error process is helping when solving the maze needs 23 actions in the median case while the random selection requires 25 actions to solve it. These results are statistically different according to a Wilcoxon–Mann–Whitney test and a p-value < 5e-4 with a Bonferroni correction.

6 ADAPTING TO DAMAGES IN THE PHYSICAL WORLD

Additionally to the experiments presented above, we are interested in evaluating the capabilities of HTE in the physical world by adapting to damages in real-time. Simulators are usually not perfect representations of the physical world and can exhibit flaws which are then reflected in learnt policies. These flaws are the reason for a reality gap that can pose challenges and needs to be overcome by the algorithm. To this end, we use the repertoires that have been learned in simulation to solve a physical maze with a real damaged hexapod.

6.1 Experimental Setup

The experimental setup consists of a 18-DoF hexapod robot and a maze (see Figure 2(a)) which is almost identical to the maze used in simulation (see Figure 4).

The hexapod robot is controlled by 15 (5 legs × 3 motors) Dynamixel motors (type XM430-W350), three per leg. We removed a leg to simulate a scenario where the robot is damaged. The experiments are run with only a single damage to the right middle leg of the hexapod (see Figure 2(b))
in contrast to the seven damages tested in simulation as a proof of concept in the real world. During the experiments, it is necessary to measure the observed behaviour of the robot, namely the position before and after a selected skill. For this purpose, we use a Vicon Motion Capture system to track the movements of the robots in our arena. The positions of the maze’s walls are known to the robot during the deployment, which are used by the MCTS planner to find the best path while avoiding collisions. The walls in our maze are mattresses that have been arranged the same way for all the experiments. We discretize our arena as a grid which allows the MCTS planner to find a path around the walls and use the vertices as way-points. The goal is to start from the right side of the maze (see Figure 16(a)) and reach the red cross on the lower left end of the maze. The configuration of the walls requires the hexapod robot to make a left turn and then a right turn which specifically tests whether the robot can adapt to damages that heavily impair turning. During all the runs, the robot is connected to our AMD Ryzen Threadripper 3970X 32-Core Processor machine via a USB cable, and we power the robot through a cable as well.

HTE and the baselines (i.e., RTE and APROL) are identical to the ones used in simulation. We train 4 distinct repertoires per method and run 4 independent evaluations per repertoire (totalling 16 runs per algorithm). Each method is evaluated by counting the number of actions the robot needs to reach the goal location (red cross in the lower left end of the mazes). In total, this requires $16 \times 5 = 80$ experiments on the physical robot. Each experiment is deemed a failure if the algorithm was not able to find a solution after 80 trials and we stopped the experiment. We observed that the robot can get stuck on corners of the maze because it is unable to turn effectively with the damaged leg. In our results we did not report experiments that failed due to the mechanical failure of the robot. In all the cases of mechanical failure, one of the metallic frames connecting the body and the legs failed due to stress caused by the missing leg.

RTE, APROL, and HTE use MCTS [Coulom 2007] for the path planning within the maze. For these experiments, we use a parallel version of MCTS [Cazenave and Jouandieu 2007] with 32 parallel roots and each tree having a budget of 100 iterations per planned action for every method. Having a fixed number of iterations per method will allow us to compare the time spent in the
planning phase as well as the complexity of the search spaces (i.e., bigger skill search space needs more planning). We directly use an existing implementation of MCTS\(^4\) in C++ for all our experiments.

### 6.2 Can We Adapt to Robot Damages in the Physical World with Policies Learned in Simulation?

Real-world applications do not only require robust actions but additionally they should be executed near real-time. For our experiments, we use 32-Cores on an AMD Ryzen Threadripper 3970X 32-Core Processor machine to run the experiments with the robot. In addition to the baselines we have introduced earlier, we also include HTE with a random secondary behaviour selection to analyse how our trial and error process works in real-world experiments similar to Section 5.5.

### Actions Needed To Solve the Maze.

In Figure 11, we show the distributions of the actions needed per variant to solve the maze in Figure 2(a). The first thing to note is that both Random HTE and HTE can solve the maze quicker than the other baselines. Among those two variants, HTE needs 26 median actions to solve the maze while Random HTE needs 32 actions. In contrast to the experiments done in simulation, it seems that RTE with a 2D repertoire is not able to adapt well to the damage while solving the maze (53 in median and 67 for the 75th percentile). During the experiments, the RTE-2D method was not able to turn well to the left due to the missing right leg which resulted in more needed actions to solve the maze. In contrast to the 2D version, the RTE-8D version seemed to benefit from the additional diversity in the repertoire (using 46 median actions). The additional diversity was helpful to overcome the damage, however having a larger skill space resulted in much longer execution times due to path planning with MCTS in the large skill space.

### Deployment Time.

Deployments in the real world benefit from quick adaptation and navigation. These benefits are the reasons why we are interested in the wall-time of each run in the physical world. Comparing execution times is subject to the hardware used during the run which is why we have the same conditions for each variant. To visualise the differences in speed for each algorithm, we plot the distributions of the duration (in seconds) in Figure 12 needed to solve the maze.

The duration includes everything from planning to the execution of the controls on the robot. From the plot we can see that the increased diversity of skills in the 8-dimensional repertoires together with the MCTS planning causes the 8D-RTE variant to be slower than the other variants. 8D-RTE needs 300\% more time than RTE-2D and 440\% more time than HTE in the mean case which is a considerable amount of time during a deployment. APROL benefits from distributing the

\(^{4}\text{https://github.com/resibots/mcts.}\)
diversity across different repertoires and is able to have results close to the RTE-8D variant in terms of actions while solving the task in less time. HTE is the fastest method due to the reduced number of actions needed and the distributed diversity via the hierarchical organisation the repertoires. The hierarchical structure allows the path planning to happen on a single layer (the top layer), which allows MCTS to finish as quick as 2D repertoires but while being able to adapt better (i.e., less actions needed to solve the maze) because of the increase diversity provided by secondary behaviours.

**Repertoire Dependencies.** We can observe that the results depend on the trained repertoire to solve the maze fast. Repertoires that have learnt locomotion skills which do not use the damaged leg will be at an advantage in comparison to repertoires that have learnt locomotion skills that heavily depend on the damaged leg. This comes back to our assumption that repertoire-based adaptation needs to have learnt a solution which is not affected by the new situation. The more diversity we have in our repertoires, the better are the chances to adapt to an unforeseen scenario. In Figure 11, we can observe the distributions of each variant across the repertoires. HTE has three of the four repertoires that need less than 28 actions in median whereas the fourth repertoire seems to be less suited to the maze/damage combination we have evaluated on the real robot. This indicates that the diversity in the HTE algorithm is good enough to overcome the maze task with damage. On the other hand, 2D-RTE in Figure 11 shows that an algorithm can be lucky during training and learn a repertoire with many well suited skills (i.e., a lot of skills do not use the damaged leg) which only needs 28 median actions to walk through the maze but unlucky for others (all repertoires perform above 50 actions in median).

The results in Figure 11 are statistically significant between all the variants and HTE, with a p-value < 3e-2 calculated with a Wilcoxon–Mann–Whitney test and a Bonferroni Correction. However, the difference between HTE with Trial and Error and HTE with random selection is not significant for the real-world experiments due to the restricted number of hardware experiments and the differences between the trained repositories. Random HTE is still quite effective in our experiments since there is a 50% chance of guessing the right secondary behaviour (i.e., each leg represents a binary choice). It is highly likely that with more choices, the Random HTE variant will not find the best secondary behaviours and might perform worse in comparison to HTE.

Finally in our experiments, HTE is not only able to adapt quicker in simulation but it can also transfer the learned skills to the physical world while still being 440% quicker than the best baseline and 43% less steps in the median case.

7 CONCLUSIONS AND FUTURE WORK

In this article, we extended the original “Hierarchical Quality-Diversity for Online Damage Recovery” [Allard et al. 2022] paper and analysed the HTE algorithm, which allows robots to learn a diversity of skills with hierarchical repertoires and use them for damage recovery both in simulation and in the physical world. HTE learns skills by splitting the complexity of the behavioural space across different layers. The introduction of primary and secondary behavioural descriptors allows HTE to learn an additional diversity of skills during training while keeping the training tractable. The secondary behavioural descriptors make it possible for the repertoire to store a larger diversity of skills than other baselines without making the training process more complex. Furthermore, we showed that the trial and error process helps to take advantage of the diversity created by the secondary behaviours.

We can effectively use this diversity in an online fashion to recover from mechanical damages while solving a maze navigation task. The results from the simulation experiments show that the damage recovery by HTE needs 14% less actions than the best baseline and, more importantly,
HTE has less complete failures (i.e., needing more than 80 actions to solve the maze). Additionally for the real-world scenarios, HTE requires 43% less actions than the best baseline while being over four times quicker in terms of execution time which is crucial for real-world experiments. In comparison to flat 2-dimensional repertoire variants, HTE has similar execution times even though it offers more diversity thanks to the hierarchy. Finally, HTE benefits from having a large diversity of behaviours while being fast in tasks requiring planning due to the reduced search space in the hierarchical structure.

One of the main limitations of this work is the definition of behavioural spaces on lower layers which heavily impacts the upper layers by restricting the search space. If the lower layers do not have enough diverse solutions, HTE will not find optimal solutions for the upper layers. Consequently, HTE requires task expertise to define different genotypes, behavioural descriptors, and fitness functions to assure a good diversity of solutions. As long as a diverse population of redundant solutions is provided, the algorithm tries to find the best one by trial and error. We refer to the experiments from Cully et al. [2015] where the authors show that the ITE algorithm works with a multitude of different behavioural descriptor definitions. The adaptation seems to be slightly quicker when the behavioural descriptor is aligned with the damage (i.e., duty cycle and leg damage) but generally the adaptation with different behaviours is still relatively quick. In every case, both manual and automatic behavioural descriptor definitions need to provide a behavioural space that is large and diverse enough for the upper layers to find more complex solutions. We have not tried any other behavioural descriptor but we think this is an interesting direction to investigate.

Our experiments are currently restricted to the Hexapod but one interesting direction of work would be to apply HTE to more real-world scenarios with different types of robots. Finally, our results show that the perfect HTE variant is better performing than HTE which might indicate that there is room for improvement in the skill selection mechanism.

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