

Robot Program Parameter Inference via Differentiable Shadow Program Inversion

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Abstract— Challenging manipulation tasks can be solved effectively by combining individual robot skills, which must be parameterized for the concrete physical environment and task at hand. This is time-consuming and difficult for human programmers, particularly for force-controlled skills. To this end, we present Shadow Program Inversion (SPI), a novel approach to infer optimal skill parameters directly from data. SPI leverages unsupervised learning to train an auxiliary differentiable program representation (“shadow program”) and realizes parameter inference via gradient-based model inversion. Our method enables the use of efficient first-order optimizers to infer optimal parameters for originally non-differentiable skills, including many skill variants currently used in production. SPI zero-shot generalizes across task objectives, meaning that shadow programs do not need to be retrained to infer parameters for different task variants. We evaluate our methods on three different robots and skill frameworks in industrial and household scenarios. Code and examples are available at <https://innolab.artiminds.com/icra2021>.

I. INTRODUCTION

Combining individual robot skills to solve complex tasks has established itself as one of the primary programming paradigms in robotics. A large variety of skill variants such as Dynamic Movement Primitives (DMPs) [1], Task and Motion Planning (TAMP) operators [2] or generalized manipulation strategies [3] have been proposed, all of which allow the behavior of skills to be adapted to the task at hand by a set of skill parameters such as velocities, scaling factors or via-points. Finding appropriate values for these parameters is difficult and typically requires manual tweaking. Consider a force-controlled spiral search skill, where the robot executes a spiral motion until a drop in forces at the tool center point (TCP) indicate that a hole has been found. The optimal parameters, i.e. spiral orientation and extents, velocity, acceleration and pushing force, to maximize the likelihood of finding a hole without sacrificing too much time, depend on the probability distribution of the hole position and the physical properties of the surfaces. For a human programmer, tuning these parameters involves much trial and error. Differentiable programming (∂P) provides an elegant solution: If a program is fully differentiable, it allows for the gradient-based optimization of program parameters with respect to nearly arbitrary objective functions over the program’s outputs [4], [5]. However, most skill libraries used in practice are not differentiable. Particularly force-controlled skills such as spiral search or moment-free insertion are often

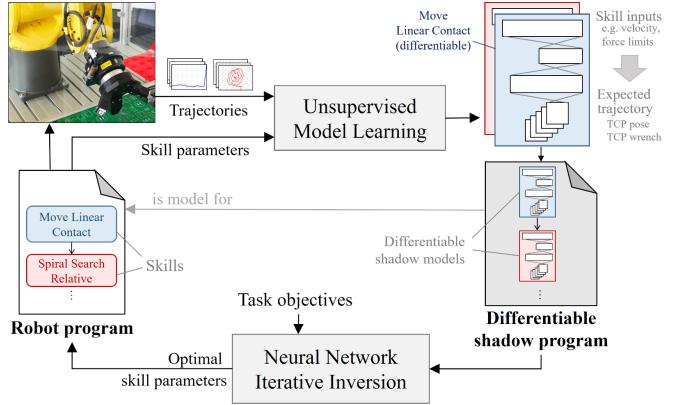


Fig. 1: Parameter inference via Shadow Program Inversion. By inverting learned differentiable shadow models (right) of a sequence of robot skills (left), optimal program parameters can be inferred directly from data.

implemented using highly performant but non-differentiable force controllers provided by robot manufacturers.

In this paper, we present Shadow Program Inversion (SPI), a novel ∂P -based method of inferring optimal parameters for robot programs of non-differentiable skills. We propose to learn a differentiable surrogate (called *shadow model*) of each skill, which is trained via unsupervised learning to predict the expected trajectory (TCP poses and wrenches) when executing the skill for a given set of parameters. Just like skills can be chained to solve complex tasks, their shadow models can be chained to form a differentiable *shadow program*. We then apply a gradient-based neural network inversion technique to the shadow program to jointly infer the skill parameters which maximize a set of task objectives. By maintaining a one-to-one relationship between the original robot skills and their differentiable shadows, the optimized program parameters can be transferred back to the original skills, which are used for execution on the robot. By conducting gradient-based parameter inference over differentiable surrogates rather than the actual skills, our method can be applied to optimize parameters for widely used skill representations such as DMPs, which do not have to be differentiable. Moreover, it generalizes in a zero-shot manner across task objectives, avoiding retraining when task objectives change. We demonstrate the broad applicability of our approach on three use cases from industrial and household robotics, involving diverse skill representations ranging from high-level generalized manipulation strategies to low-level DMPs and the URScript robot API [6]. To our knowledge, SPI is the first application of gradient-based

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model inversion to robot skill parameterization. Our main contributions can be summarized as follows:

- 1) **Shadow models**, differentiable surrogate representations of possibly non-differentiable skills.
- 2) **Shadow programs**, end-to-end differentiable representations of complete skill-based robot programs.
- 3) **Shadow Program Inversion**, an algorithm to efficiently infer optimal skill parameters via gradient-based model inversion.
- 4) **Evaluation** of Shadow Program Inversion on three different robots and real-world use cases.

II. RELATED WORK

1) *Robot skill parameter inference*: Several approaches for the automatic optimization of robot skill parameters have been proposed, which rely on gradient-free optimization techniques such as evolutionary algorithms [7], [8], [9] or Bayesian optimization [10], [11], [12] due to the non-differentiability of most skill libraries and frameworks. Gradient-free approaches require frequent execution of the skills during optimization, which is a time-consuming process if done on real robot systems, has to be repeated whenever the task objectives change and often require good initial parameterizations. We propose to use a gradient-based optimizer on a differentiable surrogate model of the skills, which avoids these issues.

2) *Unsupervised representation learning*: Recent robot learning approaches such as Visual Foresight [13], Adversarial Skill Networks [14], Time Reversal [15] or “Learning from Play” [16] propose self-supervised or unsupervised learning of a *predictive model*, i.e. a model of skill inputs to a latent trajectory representation, from which a policy to solve the task is then derived. We take a similar approach to parameterize skill-based robot programs by learning a differentiable skill model and exploit its differentiability to infer optimal program parameters. Like most approaches relying on self-supervised representation learning, ours generalizes across task variants without requiring additional training.

3) *Differentiable programming*: Differentiable programming ($\partial\mathcal{P}$) proposes to express programs as differentiable computational graphs, which permit the optimization of program parameters via reverse-mode automatic differentiation and gradient-based optimization [5], [4]. From a $\partial\mathcal{P}$ perspective, neural networks can be considered a type of differentiable program, and can be combined to computational graphs-of-networks [17], [18], [19] as well as hybrid architectures combining neural networks with differentiable hand-written algorithms or data structures [20], [21], [22], [23], [24]. In the domain of robotics, $\partial\mathcal{P}$ has been realized in the form of hybrid skill representations such as Conditional Neural Movement Primitives [25], [26], Deep Movement Primitives [27] or Differentiable Algorithm Networks [28], which combine differentiable algorithmic priors with neural networks and can be combined to complex robot programs in a modular fashion. Like most prior work on $\partial\mathcal{P}$ in robotics, we provide modular interfaces to combine differentiable

functional blocks to complex programs, and combine hand-written computational graphs with neural networks to simplify the learning problems. In contrast to prior work, however, we rely exclusively on unsupervised learning, which greatly simplifies data collection and model training. In work similar to ours, Zhou et al. [29] propose to generate DMP parameters directly with a Mixture Density Network. We instead propose to learn a differentiable model of the DMP and to infer the optimal skill parameters via model inversion after training. The advantage is that no retraining is required when the task objective changes. Moreover, our approach can be applied to near-arbitrary skill representations beyond DMPs and allows the optimization of parameters for complex programs composed of multiple skills.

III. DEFINITIONS & PROBLEM STATEMENT

A. Definition: Skill-based Robot Program

We define a skill-based robot program as a directed acyclic graph (DAG) of skills, where each skill is defined as a function $f : \mathcal{X} \times \mathcal{S} \rightarrow \mathcal{S} \times \mathcal{Y}$ with the space of the skill’s exposed input parameters \mathcal{X} , \mathcal{S} the state space comprising the current poses of coordinate frames relevant to the task and \mathcal{Y} the trajectory space comprising TCP poses and wrenches. This definition allows to treat a skill as a black box which maps a vector of inputs $\mathbf{x} \in \mathcal{X}$ and prior state $s_{in} \in \mathcal{S}$ to posterior state $s_{out} \in \mathcal{S}$ and trajectory $\mathbf{Y} \in \mathcal{Y}$. It covers DMPs [1], generalized manipulation strategies [3] or any skill variant which takes some inputs \mathbf{x} and moves the robot. This definition allows to design a universal differentiable shadow model architecture capable of representing them.

B. Problem Statement: Robot Program Parameter Inference

Sequentially chained skills form complex robot programs by propagating the posterior state $s_{i,out}$ of the i th skill in the sequence to the prior state $s_{i+1,in}$ of the subsequent skill. We postulate the Markov property, i.e. all relevant context information is captured in the start state s_{in} . Such a skill-based robot program realizes the function $P : \mathcal{S} \times \mathcal{X}^n \rightarrow \mathcal{S} \times \mathcal{Y}$. We seek to optimize a task-dependent objective function $\Phi : \mathcal{Y} \rightarrow \mathbb{R}$, which assigns a real-valued score to a trajectory. For a program containing a spiral search skill, Φ might assign high scores to trajectories which exhibit the characteristic drop in forces indicating that the hole has been found. For a given program P and initial state s_{in} , we seek to solve the inverse problem $\mathbf{x}^* = \text{argmax}_{\mathbf{x} \in \mathcal{X}^n} \Phi(P(s_{in}, \mathbf{x}))$, i.e. to find skill parameters which maximize Φ . In the spiral search example, \mathbf{x}^* contains the velocities, accelerations, spiral extents and force setpoints which maximize the likelihood of the hole being found. Due to the high dimensionality of the combined input space \mathcal{X}^n of complex programs, learning to directly compute \mathbf{x}^* would require prohibitive amounts of supervised training data. We propose to instead train a differentiable model \hat{P} (called *shadow program*) of P , and to iteratively approximate \mathbf{x}^* by gradient descent over \hat{P} .

IV. PARAMETER INFERENCE VIA SHADOW PROGRAM INVERSION

We propose a three-step process to infer skill parameters for a skill-based robot program: (1) Construction of a differentiable surrogate (shadow program, \hat{P}), which predicts the expected trajectory (TCP poses and wrenches) given input parameters for all skills in the program; (2) unsupervised training of the learnable components of this surrogate; and (3) inference of optimal skill parameters via gradient-based model inversion (cf. figure 1).

A. Shadow Model & Shadow Program Architecture

For a given skill-based robot program (such as a sequence of DMPs) P , whose parameters are to be inferred, we begin by constructing the differentiable shadow program \hat{P} . To that end, we instantiate a differentiable *shadow model* for each skill in P . Because we only consider skills which meet definition III-A, we can propose one single, differentiable shadow model architecture which can model any skill. This architecture is illustrated in figure 2.

A shadow model of the i -th skill in a skill-based robot program is a differentiable computational graph which computes the expected trajectory \hat{Y}_i for a given input vector x_i and start state $s_{in,i}$. We represent \hat{Y}_i as a sequence of samples $(\hat{Y}_i)_t$, $0 \leq t < |\hat{Y}_i|$, each of which contains the current success probability $p_{succ} \in [0, 1]$, the probability $pEOS \in [0, 1]$ of the action being completed at time t , as well as the TCP pose and wrench at time t . In figure 2, x_i contains the input parameters of a force-controlled spiral search skill, and $s_{in,i}$ is set to the final state $s_{out,i-1}$ of the previous skill. The inclusion of p_{succ} in \mathcal{Y} permits the inference of skill parameters with respect to skill-specific success metrics. For a spiral search, it allows to specify an objective function to maximize the probability of finding the hole (cf. equation 3 and experiment V-C).

Echoing work in $\partial\mathcal{P}$ integrating algorithmic priors and deep learning [30], [24], we do not predict the expected trajectory \hat{Y}_i end-to-end. Instead, we bootstrap an initial prior trajectory estimate \tilde{Y}_i using a differentiable motion planner,³ which produces a crude approximation of the trajectory without interactions with the environment such as moving objects or applying contact forces. We found that explicitly incorporating prior knowledge greatly reduced the amount of training data required, particularly for long trajectories. For skills for which no such algorithmic prior exists, we instead use a generative neural network to bootstrap a prior trajectory from x_i and $s_{in,i}$ [34]. The posterior trajectory \hat{Y} is the sum of the prior and the output of a deep residual Gated Recurrent Unit (GRU) [35], which predicts the residual trajectory $\hat{Y}_{res,i}$ containing the context-dependent information about interactions with the environment, such as (expected) forces and torques. For the spiral search skill, for example, the residual GRU learns to predict when and where a hole is

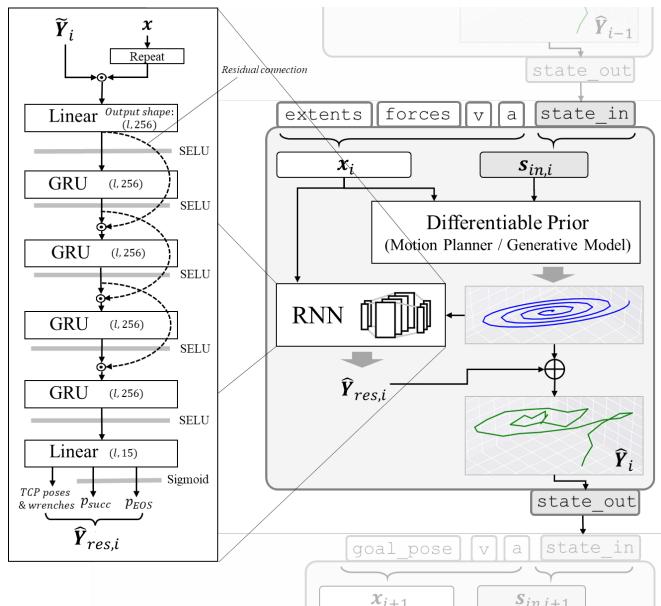


Fig. 2: A shadow model of a spiral search skill as part of a larger shadow program.

likely to be found, and how the expected trajectory then deviates from the prior \tilde{Y}_i .

The shadow model architecture is sufficiently flexible to model simple and complex skills with varying numbers and types of parameters. Note that the “signature” (layout of the parameter vector \boldsymbol{x}) of a shadow model exactly matches that of the skill it models. This permits the transfer of the inferred parameters back to the original skill after inference (cf. IV-C). Aside from the optional differentiable motion planner, which will differ from skill to skill, the proposed shadow model architecture can model any skill which meets the skill definition in section III-A. This allows the automatic construction of a shadow program for any complex skill-based robot program by instantiating a shadow model for each skill, and connecting the posterior state s_{out} of each shadow model to the prior state s_{in} of the next.

B. Unsupervised Shadow Model Learning

Because shadow models are forward models of semi-symbolic skills, they can be trained end-to-end on tuples $(\mathbf{x}, s_{in}, \mathbf{Y})^4$ to minimize the mean prediction error

$$\begin{aligned} \mathcal{L}_{pred}(\hat{\mathbf{Y}}, \mathbf{Y}) = & \frac{1}{|\hat{\mathbf{Y}}|} \sum_{n=1}^{|\hat{\mathbf{Y}}|=|\mathbf{Y}|} (w_{pos} \mathcal{L}_{L2}((\hat{\mathbf{Y}})_{n, pos}, (\mathbf{Y})_{n, pos}) \\ & + w_{ori} \mathcal{L}_{ori}((\hat{\mathbf{Y}})_{n, ori}, (\mathbf{Y})_{n, ori}) \\ & + w_{ft} \mathcal{L}_{L2}((\hat{\mathbf{Y}})_{n, ft}, (\mathbf{Y})_{n, ft})) \quad (1) \\ & + w_{succ} \mathcal{L}_{BCE}((\hat{\mathbf{Y}})_{n, p_{succ}}, (\mathbf{Y})_{n, p_{succ}}) \\ & + w_{EOS} \mathcal{L}_{BCE}((\hat{\mathbf{Y}})_{n, p_{EOS}}, (\mathbf{Y})_{n, p_{EOS}})), \end{aligned}$$

a weighted sum of the squared pointwise L2 distance \mathcal{L}_{L2} for TCP position and wrench, the pointwise binary crossentropy

³For our experiments (see section V), we implemented simple differentiable planners for linear motions, spiral motions and gripper motions by reimplementing parts of orocos-kdl [31] and urdfpy [32] with PyTorch [33].

⁴In our implementation, s_{out} can be deterministically computed from the output trajectory \hat{Y} and does not need to be learned explicitly.

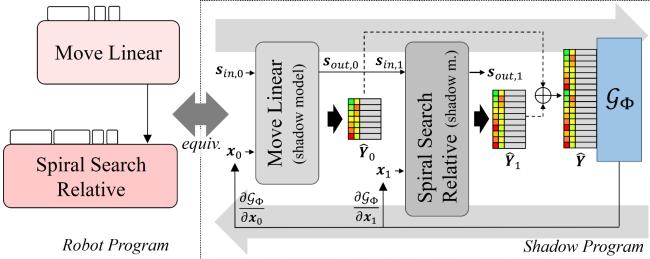


Fig. 3: SPI (right) permits inference of skill parameters (\mathbf{x}_0 and \mathbf{x}_1) w.r.t. task objectives G_Φ for non-differentiable robot programs (left).

loss \mathcal{L}_{BCE} for p_{succ} and p_{EOS} , and the pointwise angle between quaternion-encoded TCP orientations

$$\mathcal{L}_{ori}(\hat{\mathbf{y}}, \mathbf{y}) = \cos^{-1}(2\langle \hat{\mathbf{y}}_{ori}, \mathbf{y}_{ori} \rangle^2 - 1). \quad (2)$$

$\langle \mathbf{q}_1, \mathbf{q}_2 \rangle$ denotes the inner product of quaternions \mathbf{q}_1 and \mathbf{q}_2 . $(\mathbf{Y})_{n, pos}$ denotes the position component of the n -th point on trajectory \mathbf{Y} . Training data can be collected autonomously by sampling inputs \mathbf{x} and initial states s_{in} , executing the original (non-differentiable) skills and recording the resulting trajectories. In real-world settings, in which programs are executed repeatedly over long periods of time, this permits the efficient use of readily available unsupervised data and facilitates automatic finetuning of the model as new observations become available. Because of the Markov property, shadow models can be trained separately from one another, conditional on the start state s_{in} , to form a library of trained, differentiable shadow models.

C. Gradient-based Shadow Program Inversion

To infer optimal parameters for a given skill-based robot program, we construct the corresponding shadow program by sequentially chaining trained shadow models via s_{in} and s_{out} (see figure 3). The shadow program is a differentiable graph-of-graphs; its differentiability permits the efficient, gradient-based optimization of the input parameters $\mathbf{x}_i, 0 \leq i < n$ of all n skills of in the program with respect to an arbitrary, differentiable objective function G_Φ for task objectives Φ . To perform this optimization, we use Neural Network Iterative Inversion (NNII) [36]: We randomly initialize the \mathbf{x}_i , perform a forward pass and compute the loss $G_\Phi(\hat{\mathbf{Y}})$. We exploit the differentiability of the program graph to backpropagate the gradients $\frac{\partial G_\Phi(\hat{\mathbf{Y}})}{\partial \mathbf{x}_i}$ and update the \mathbf{x}_i according to the Adam update rule [37]. Iterating until convergence yields the \mathbf{x}_i which minimize G_Φ .

With differentiability w.r.t. $\hat{\mathbf{Y}}$ the sole requirement, a wide range of objective functions can be applied. In an industrial context, typical optimization targets include process metrics such as cycle time (\mathcal{G}_{cycle}), failure rate (\mathcal{G}_{fail}) or path length (\mathcal{G}_{path}). The inclusion of meta information p_{EOS} and p_{succ} in $\hat{\mathbf{Y}}$ permits the succinct expression of the corresponding objective functions:

$$\mathcal{G}_{fail}(\hat{\mathbf{Y}}) = -\max\left(0, \min\left(\frac{1}{|\hat{\mathbf{Y}}|} \sum_{n=1}^{|\hat{\mathbf{Y}}|} (\hat{\mathbf{Y}})_{n, p_{succ}}, 1\right)\right) \quad (3)$$

$$\mathcal{G}_{cycle}(\hat{\mathbf{Y}}) = \sum_{n=1}^{|\hat{\mathbf{Y}}|} \left(1 - \sigma((\hat{\mathbf{Y}})_{n, p_{EOS}} - 0.5) * T\right) \quad (4)$$

$$\begin{aligned} \mathcal{G}_{path}(\hat{\mathbf{Y}}) = \frac{1}{|\hat{\mathbf{Y}}|} \sum_{n=1}^{|\hat{\mathbf{Y}}|-1} & \left(\|(\hat{\mathbf{Y}})_{n+1, pos} - (\hat{\mathbf{Y}})_{n, pos}\| \right. \\ & \left. + \mathcal{L}_{ori}((\hat{\mathbf{Y}})_{n+1, ori}, (\hat{\mathbf{Y}})_{n, ori}) \right) \end{aligned} \quad (5)$$

σ is the sigmoid function, T a constant (here $T = 100$) and \mathcal{L}_{ori} as defined in eqn. 2. Joint optimization of multiple metrics at the same time can be realized by linear combination. SPI as described above has several properties which make it both theoretically attractive and practically applicable in real-world scenarios:

1) *Asymptotic optimality*: If G_Φ is the objective function of the equivalent minimization problem to $\text{argmax}_x \Phi(P(s_{in}, x))$, x will approximate the optimal parameters x^* , provided G_Φ is convex, P is faithfully approximated by the shadow program, gradients are bounded and the learning rate is small [37]. In practice, near-optimal solutions can be reached in a few hundred iterations.

2) *Separation of learning from inference*: Because the learning problem is reduced to learning a forward model of the program, parameter inference is decoupled from training and therefore very fast. Individual shadow models can be trained offline and combined to arbitrary shadow programs at inference time. Parameter inference itself does not require additional training, exploration or expensive policy search.

3) *Zero-shot generalization*: By extension, our approach permits parameter inference with respect to arbitrary objective functions without requiring additional training examples. The same robot program can be optimized for different task objectives Φ by simply changing the loss function G_Φ accordingly and rerunning NNII.

V. EXPERIMENTS

To evaluate our approach in a wide variety of real-world applications, we apply SPI to infer program parameters from human demonstrations for pick-and-place tasks in a household scenario, impact force optimization for contact motions and the inference of spiral search heuristics in the context of electronics assembly.

A. Parameter Inference for Complex Task Objectives

In this experiment, we demonstrate the capacity of SPI to infer parameters with respect to complex task objectives from scratch. To that end, a household task of picking up a glass and depositing it in a sink is considered. Given only a program structure (a sequence of unparameterized skills), a set of parameters is to be inferred which closely approximates a human demonstration of the task. The program consists of a linear approach motion, opening the gripper, a sequence of 3 linear transfer motions, a skill to close the gripper and a linear depart motion.⁵ Skill parameters are

⁵The skill representation for which parameters are inferred in experiments V-A, V-B.1 and V-C is the ArtiMinds Robot Task Model (ARTM) [38], a non-differentiable industrial implementation of generalized manipulation strategies [3].

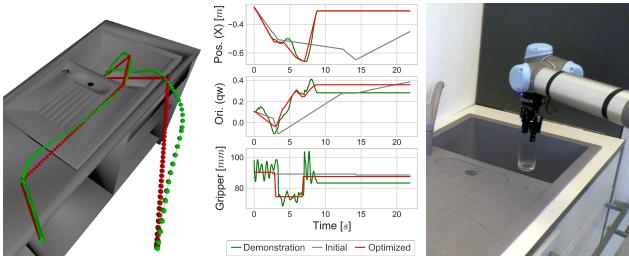


Fig. 4: Experiment V-A: Human demonstration (green) and trajectory after parameter inference (red) in 3D (left); 2D projections onto a position and orientation dimension and the gripper opening (middle); real-world execution (right).

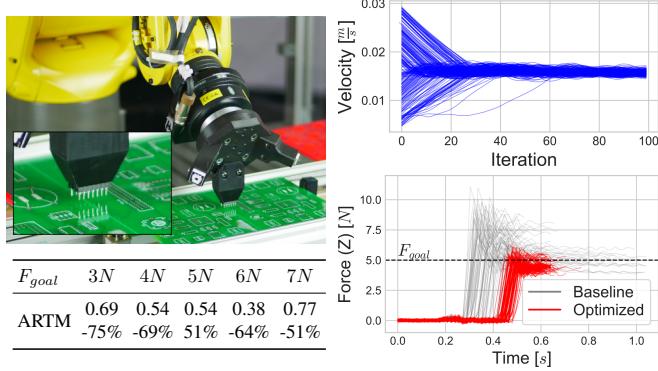
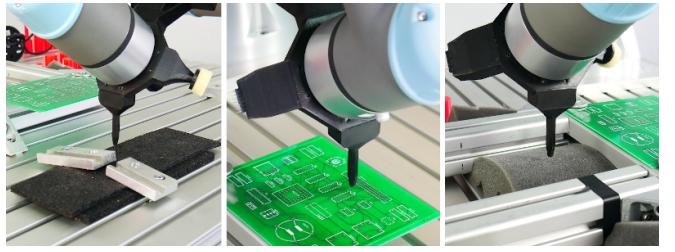


Fig. 5: Experiment V-B: Optimization of contact motions (bottom left). Each cell shows the mean deviation from F_{goal} over 250 optimizations and the improvement over the initial parameterization. Right: Convergence behavior of SPI for the velocity parameter and resulting force trajectories for $F_{goal} = 5 \text{ N}$ for a linear motion ARTM skill.

initialized randomly and comprise the goal poses, velocities and accelerations of the linear motions as well as the target joint state and velocity of the gripper skills. Program parameters were inferred to minimize a combination of pointwise distance \mathcal{G}_d between the TCP and the demonstration as well as the demonstrated and predicted hand openings, and a grasp penalty \mathcal{G}_g enforcing additional precision during grasps. Minimizing \mathcal{G}_d and \mathcal{G}_g is a challenging optimization problem because the dynamics of the demonstration and predicted trajectories are vastly different, and SPI must implicitly adapt the velocities and accelerations of the skills first in order to make the predicted trajectories comparable to the demonstration. Four human demonstrations were collected in virtual reality (VR) using the KnowRob framework [39]. For this use case, the gripper state was included in \mathcal{S} and \mathcal{Y} . Real-world experiments were conducted using a Universal Robots UR5 industrial manipulator and a Robotiq 2FG-85 parallel gripper. Results are shown in figure 4. For each of the four demonstrations, parameter inference results in a robot motion which closely approximates the human demonstrations, but obeys the constraints such as linearity imposed by the skills. The results testify to the capacity of SPI to jointly infer skill inputs for realistic robot programs, even if the initial program parameters are far from the optimum.



F_{goal}	Rubber			PCB			Foam		
	5N	10N	20N	1N	5N	8N	1N	1.5N	2N
URScript	1.43 -75%	1.63 -84%	2.76 -84%	0.16 -92%	0.68 -71%	0.95 -80%	0.24 -36%	0.15 -51%	0.16 -74%
DMP	0.56 -96%	0.65 -94%	2.55 -85%	0.14 -90%	0.18 -93%	0.26 -95%	0.16 -60%	0.21 -54%	0.17 -78%

Fig. 6: Experiment V-B.2: Optimization of contact motions for different skill frameworks and surfaces. Each cell shows the mean deviation from F_{goal} over 100 optimizations from random initial parameters (in N) and the improvement of this error over the initial parameterization.

B. Force-Sensitive Manipulation Without Expert Knowledge

1) *Data-driven optimization of contact forces:* To evaluate our approach in the context of industrial manipulation, we consider the task of touching a surface with a specific impact force. In a first series of tests, we use SPI to optimize the motion direction, velocity v and acceleration a of a linear contact motion skill, which moves the robot in a given direction until a force F_{goal} is registered. Contact motions are difficult to parameterize manually because the true contact force $F_{contact}$ is determined by a spring-mass-damper system composed of the robot and the contact surface with unknown dampening and spring characteristics. F_{goal} merely imposes a lower bound on the maximum force, with v and a determining the true force on contact (cf. figure 5 (gray)). A shadow model was trained on 50000 simulated and 500 real executions with randomly sampled values of v and a . The task objective consisted of a linear combination of \mathcal{G}_{cycle} and the mean squared error between the predicted contact force and F_{goal} . We ran SPI for goal forces between 3 and 7 N, collecting 250 inferred parameterizations for each goal force and randomly initializing v and a . A total of 1250 optimized programs were executed on a Fanuc LR Mate 200iD/7L manipulator and FS-15iA force-torque sensor (FTS).

For goal forces between 3 and 5 N, the optimized parameterizations produce maximum contact forces very close to the target force (cf. figure 5, bottom left), demonstrating the capability of our approach to zero-shot generalize across task objectives (in this case, different values of F_{goal}). Figure 5 (top right) illustrates the convergence behavior of our optimizer for a goal force of 5 N, which converges on a globally optimal velocity in under 40 NNII iterations regardless of the initial parameterization. Figure 5 (bottom right) shows the force trajectories resulting from executing the 250 resulting parameterizations.

2) *Generalization to different skill representations*: In a second series of experiments, we use SPI over shadow skills to parameterize low-level primitives with respect to three different surfaces with very different dampening characteristics. To illustrate the universality of SPI, we optimize the target pose, velocity and acceleration parameters of the `moveL` URScript primitive [6] as well as the temporal scaling parameter τ and the target pose of a linear discrete DMP [40] to establish F_{goal} . The experiments were conducted on a Universal Robots UR5e. The results summarized in table 6 show that the inferred parameterizations produce contact forces well within $0.25 N$ of the goal on most surfaces, which is in the order of sensor noise. For both DMPs and URScript skills, SPI could adapt parameters to dampening characteristics ranging from near-linear (foam) to highly nonlinear (rubber) for a wide range of contact forces.

C. Zero-Shot Generalization Across Task Objectives

To illustrate the capacity of SPI to zero-shot generalize across task objectives, we consider a further use case of finding the position of a set of holes on a printed circuit board (PCB) for the insertion of electronics components. In practice, manufacturing tolerances cause stochastic deviations from the expected hole positions on the order of millimeters, requiring the use of force-controlled search motions. A program structure to solve this task consists of a linear approach motion followed by a force-controlled spiral search (cf. figure 3). The spiral search skill accepts inputs w_x and w_y defining the extents of the spiral motion along its principal axes, the distance d between spiral arms, force runtime constraints F_{min}, F_{max} , position goal constraints z_{min}, z_{max} , velocity v and acceleration a and performs a spiral motion in the xy-plane of the TCP, maintaining a force between F_{min} and F_{max} along the z-axis of the TCP, succeeding if a depth between z_{min} and z_{max} can be reached. Shadow models for both skills were pre-trained on 50000 simulated executions and fine-tuned on 2500 real samples using a Fanuc LR Mate 200iD/7L and FS-15iA FTS. We collected two baseline test datasets of 250 samples each, one with randomly initialized input parameters and one parameterized by a human expert. Parameter inference was conducted from initial input parameters set to the respective baseline parameterization. To demonstrate zero-shot generalization across task objectives, program parameters were optimized with respect to \mathcal{G}_{cycle} , \mathcal{G}_{fail} , \mathcal{G}_{path} (cf. 4) as well as linear combinations.

The optimized parameterizations consistently yield improvements for their corresponding metrics (cf. figure 7). Compared to the already robust human expert parameterization, the optimized parameterization nearly eliminates failures altogether. Joint parameter inference with respect to a combination of task objectives yields gains in both metrics. Figure 7 shows examples for spiral motions resulting from the optimized policies. Optimization with respect to different task objectives results in fundamentally different search policies, such as a “fail fast” policy for minimizing path length or a very robust policy for minimizing failure rate and cycle time which near-optimally fits the hole distribution.

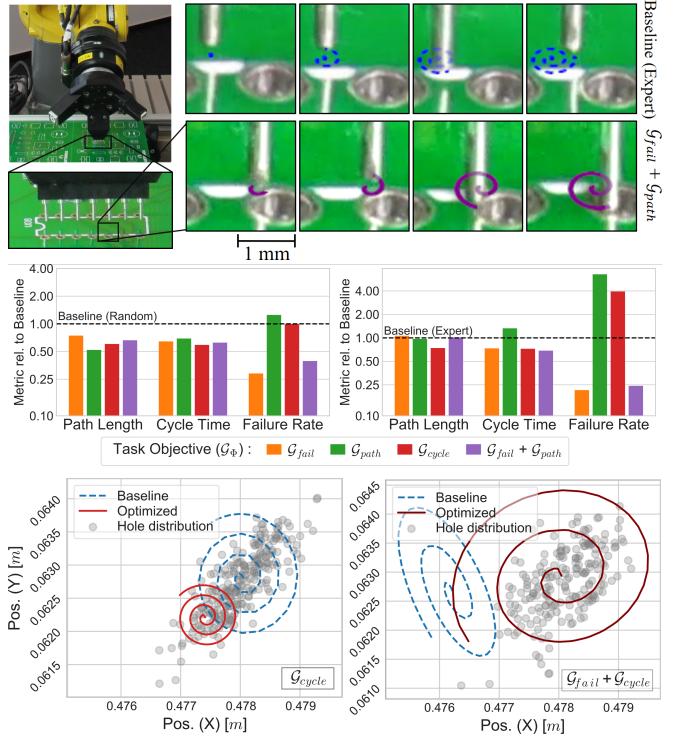


Fig. 7: Experiment V-C: Top: Stochastic variations of the hole position cause a manually parameterized spiral search to fail, while an inferred parameterization is more robust. Middle: Process metrics for optimized programs relative to random (left) and expert (right) baselines (log scale). Bottom: Spiral search policies for different objective functions.

VI. CONCLUSION AND OUTLOOK

We present an approach for inferring the input parameters of skill-based robot programs by a combination of unsupervised learning and gradient-based iterative model inversion. To our knowledge, this is the first application of differentiable programming and NNII to the skill parameterization problem in robotics. We show that SPI can effectively infer optimal parameters for robot programs composed from non-differentiable skill frameworks. Application to force-sensitive contact motions and search heuristics for electronics assembly demonstrate its capability to adapt parameters to nonlinear system dynamics or stochastic process noise. Zero-shot generalization across task objectives and exclusive reliance on unsupervised training establish SPI as a powerful solution for parameter inference in real-world use cases. Like all first-order optimization methods, the performance of SPI is conditional on the topology of the objective function. We are investigating the possibility of augmenting NNII by hessian-free optimization to further improve performance [41]. We further observe that reinforcement learning (RL)-based robot learning approaches require a solution to locally optimize skill parameters [42], [43], motivating further inquiry on synergies between SPI and RL for robot learning.

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