Predicting Physical Object Properties from Video

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Abstract—We present a novel approach to estimating physical properties of objects from video. Our approach consists of a physics engine and a correction estimator. Starting from the initial observed state, object behavior is simulated forward in time. Based on the simulated and observed behavior, the correction estimator then determines refined physical parameters for each object. The method can be iterated for increased precision. Our approach is generic, as it allows for the use of an arbitrary—not necessarily differentiable—physics engine and correction estimator. For the latter, we evaluate both gradient-free hyperparameter optimization and a deep convolutional neural network. We demonstrate faster and more robust convergence of the learned method in several simulated 2D scenarios focusing on bin situations.

Index Terms—System identification, physics simulation, physical parameters, iterative refinement

I. INTRODUCTION

Many tasks in robotics and autonomous systems require a reliable model of the world that is surrounding the agent. Notably, this includes a model of the physical properties of foreign objects: Mass, surface friction, elasticity, moment-of-inertia, and density distribution/center-of-mass can all play a crucial role and—when guessed incorrectly—lead to failure cases. One prominent example application is bin picking [1], [2], where a robotic agent has to detect and manipulate objects.

We explore ways to improve the knowledge of physical parameters of objects, as illustrated in Fig. 1. One way to achieve this is the use of a physics engine which in itself is differentiable and therefore allows for backpropagation of observed errors between simulation and reality through the engine, in order to update the physical parameters of a simulation. In this work, we investigate a more flexible approach: We propose a framework that uses a correction estimator—e.g. a neural network—to refine the physical parameters in a simulation iteratively, by comparing an observation to the simulation. Since we treat the physics engine as a black box, we remove the need for differentiability and instead rely on well-understood neural network and machine learning techniques. This simplification allows for the use of commercially available physics engines that are already optimized for speed and efficiency but are not necessarily differentiable.

Our contributions include 1) a general iterative framework for optimization of physical object parameters and 2) a thorough evaluation of learning-based and task-agnostic approaches for the correction estimator.

II. RELATED WORK

The task of predicting physical parameters of objects has been investigated before, for example from short video sequences in an unsupervised fashion [4]. Often, properties are also predicted from single pictures, for example via micro-CT pictures for porous media [5], pictures of stacked crops [6], or pictures of liquid crystals [7]. In a more robotics-centric context, neural networks have been used to predict the hardness of objects with a GelSight sensor [8] and to identify parameters of unmanned aerial vehicles [9]. In contrast to these earlier works, our dynamic approach utilizes iteration over observed scenes, which allows for constant refinement of the parameters by taking into account new information.

One application of our technique is bin picking. Here, the success of planned operations is critically dependent on how well a robotic agent can be controlled. Often, controllers are optimized in simulated environments with reinforcement learning, particle swarms, or genetic algorithms, completely free of any derivatives [10]–[12]. As a consequence, the robot is often treated as black box, which prevents the use of efficient gradient-based deep learning methods. Physics
III. METHOD

Our approach to predicting the physical parameters of objects is inspired by earlier work on iterative prediction of pose estimation [3]. In summary, we observe the scene as a sequence of video frames and try to estimate the physical properties by producing a simulated scene with guessed parameters. Importantly, this approach separates the simulation from the task of predicting the input parameters. In comparison to approaches where the simulation itself has to be differentiable, we can independently choose which physics engine we use for simulation and how to optimize the parameters. This principle is illustrated in Fig. 2. Starting from an initial guess of the parameters $p_1^{(0)}, \ldots, p_n^{(0)}$, we simulate the scene. Note that we assume some sort of pose estimation that gives us the capability to match the observable system state, so that we can start the simulation in the same configuration as seen in the first observation frame.

Both sequences of pictures, observed and simulated, are then passed to the correction estimator, which outputs a set of parameter changes $\Delta p_n^{(t)}$ for all $n$ parameters entering the simulator. These parameter changes are then added to the initial parameters to yield the updated simulation parameters.

The process can be iterated as often as needed: The updated parameters can be used for the next simulation. In summary, each iteration consists of one forward pass through the simulator and one pass through the correction estimator. One important question is how our approach should treat different numbers of objects in the scene. When predicting physical parameter changes, the naive approach would be to predict all parameter updates at the same time. However, since the shape of the output is fixed at runtime, this would mean the network is only usable for a fixed number of objects. In our case, we decided to gain flexibility by predicting parameter changes for objects one at a time. We select the object of interest on the input by marking it with a different color, see Fig. 3. In the bin picking use case, this would amount to an initial segmentation task that can either be performed separately, or by the correction estimator itself. Comparing the single-object and multi-object approaches, no significant difference in performance was observed. An alternative approach to color-marking would be to place the objects themselves in separate channels, e.g. by instance segmentation.
Frame 5
Frame 25
Time
Frame 5
Frame 25
(a) Three colliding circles  
(b) Second-order collision  
(c) Stacked Boxes  
(d) Bouncing Balls

Fig. 3. Experimental scenes.

Fig. 4. Architecture of the learned correction estimator. The batch dimension is omitted.

A. Simulator Module

In principle, with our approach, the choice of the physics engine is arbitrary. For testing in a two-dimensional environment, we chose the Python-based physics library Pymunk\(^2\), which is built on the physics engine Chipmunk\(^3\). The library allows for efficient simulation of two-dimensional rigid-body physics. Objects can be defined with arbitrary (two-dimensional) shapes, represented through polygons. Other physical properties like the mass, center-of-mass, moment of inertia, elasticity, and friction can be set as well, which allows for several different parameters to be predicted by our framework. Forces can be added to objects, which allows for dynamical behavior. Fixed (immovable) objects can be added to the scene that can act as barriers. Pymunk includes helper functions for visualization with pygame\(^4\), which allows for prototyping and visualization of our test scenes.

B. Correction Estimator

One possible choice for the correction estimator is to use generic gradient-free optimization techniques. In our case, we employ the hyperopt library [19] for Python, which implements a Tree of Parzen Estimators (TPE) approach to find the optimal set of parameters for a given objective function [20]. The objective function has to take the parameters as input and provide a measure for the accuracy of the output. As a criterion for accuracy, we choose the mean squared error between the ground truth and simulated time series in image-space. Hyperopt logs arbitrary measures during the optimization cycle and provides the best set of parameters after optimization. We expected that Hyperopt gives a reasonable baseline for optimization.

An alternative choice for the correction estimator is to use a neural network, which learns the task of predicting optimal parameter updates. The expectation is that a learned estimator can exploit the characteristics of the underlying system much better than a generic optimizer.

Image-like representations and their time series are well-suited as an input representation, since they are readily available in our application domain (e.g. from semantic segmentation of the scene) and contain the necessary details, such as object position and contact information. Therefore, our network directly operates on this representation. The network architecture closely resembles a ResNet-18 architecture [18], however, we use 3D convolutional layers to accommodate for the time series collection of pictures (see Fig. 4). The input to our network has the shape \((B \times 2T \times C \times Y \times X)\), where \(B\) is the batch size (10 or 20, with no discernable difference in performance), \(2T\) the length of the concatenated time series (usually \(2 \times 30 = 60\)), \(C\) the number of color / object channels and \(Y \times X\) the resolution of the frames. We furthermore found that in our case, dropout regularization leads to more stable results as compared to the usually employed batch normalization. The network is trained to predict correction estimates between randomly chosen parameters (\(p\) and \(p'\) for observation and guess time series, respectively) for a randomly chosen object in the scene. The loss function is the mean

\(^2\)http://www.pymunk.org
\(^3\)http://chipmunk-physics.net
\(^4\)https://www.pygame.org
We note that the required forward passes may be performed through the prediction module, it allows for more flexibility. Tested and were found to yield similar performance. While the investigated object in a different image channel, or fix for the highlighted object. Alternative approaches are to place color. The correction estimator then predicts parameter updates for the objects present in the scene, we highlight one of the objects by old value with the parameter update \( p_{i}(t+1) = p_{i}(t) + \Delta p_{i} \).

C. Multiple Objects

To keep our approach flexible with regards to the number of objects present in the scene, we highlight one of the objects by color. The correction estimator then predicts parameter updates for the highlighted object. Alternative approaches are to place the investigated object in a different image channel, or fix the output dimension to allow for simultaneous prediction of several objects’ properties. Both approaches have been tested and were found to yield similar performance. While highlighting single objects requires \( N_{\text{obj}} \) more forward passes through the prediction module, it allows for more flexibility. We note that the required forward passes may be performed in parallel.

IV. EVALUATION

We evaluate our approach in two different scenarios with different combinations of predicted parameters and object configurations—a simple bin configuration and a more complex pool table setup. We compare the performance of Hyperopt and the neural network as correction estimator. Our measure of performance is the minimum achieved mean squared error between guessed and real parameters. To be able to compare different parameters with different number ranges, each parameter is normalized by its maximum achievable value. In case of unknown ground truth values, the minimum achieved error can be found by comparing the mean squared error between the time series, similar to the objective function of the Hyperopt approach. Throughout our testing, runtime was dominated by physics simulation, not correction estimation. As a consequence, the number of iterations needed to find good parameters directly measures the performance of the approach for the correction estimator.

The learning-based estimator was trained using the Adam optimizer (learning rate \( 5e^{-6} \)) on 130000 simulated scenes. We note that this does not need to be trained on a specific scene configuration. The required training time can thus be done before deployment in a particular application.

A. Objects in a Bin

The first investigated scene is inspired by bin picking scenarios. It consists of a two-dimensional box formed by immovable lines, with three objects placed in it. One of the observed objects is a test object with constant physical parameters throughout all scene iterations. This object fixes the numerical value for the other objects, as the collisions dynamics between objects only depends on the ratio between their physical parameters. All objects are subject to gravitational force, and the test object is additionally accelerated towards the other objects. In this scenario, we investigate three different scenes: 1) Three circles, where the test object is accelerated towards the two unknown object from above, 2) second-order collisions, where the test object is accelerated from one direction towards one of the unknown objects, which then interacts with the other unknown object and 3) stacked boxes, with two square-shaped objects stacked on top of each other, where the circular shaped test object is accelerated towards the stacked objects. These scenes are depicted in Fig. 3 (a) to (c).

To verify predictiveness of the different physical parameters, we investigate how the mean squared error between the raw time series changes for different values of the predicted parameters, see Fig. 5, topmost row. This analysis shows, that for both mass and elasticity, a gradient towards small parameter changes always exists (albeit smaller for mass). For friction on the other hand, the curve looks flat above a certain threshold. This can be explained by physical considerations: To first order the collisional dynamics of rigid circles does not depend on the surface friction, therefore, changing the friction does not influence the trajectory of the objects. Fig. 5 also shows the difference between the final frames of the compared timeseries for different parameter values. This highlights the necessity for expressive dynamics, that yields information about the physical parameters under investigation.

Fig. 5. Image-space MSE between two full time series with different physical parameters. The parameter under investigation is fixed to a specific value \((m_1 = 5 \text{ and } f_1 = e_1 = 0.1 \text{ for mass, friction, and elasticity})\) for one of the time series and varied for the other \((p_2 = p_1 + \Delta p \text{ for } p \in \{m, e, f\})\). The pictures in the lower three rows show the difference between the last frame of each time series, respectively. The grey dashed lines in the top three plots indicate the values of the pictures in the bottom three rows (each panel in the first row from left to right represents a row from top to bottom).
We train the network on each scene separately on randomly chosen parameters to predict parameter changes. To evaluate the performance, we generate new scenes with random parameters and predict parameter updates for each mass starting with a random guess. We then resimulate and iterate this procedure. We find that our approach generally converges towards its final value after one or two iterations, see Fig. 7. For comparison, we test generic hyperparameter optimization to predict the parameters, which finds comparably good values after an order of magnitude more iterations, see Fig. 7 (bottom). This is also highlighted in parameter space, where the Hyperopt approach performs much more exploration, see Fig. 6. The best value after 11 iterations for each tested scene / parameter combination is shown in Table I. In agreement with the results of Fig. 5, we found that for some combinations of scenes and parameters, the performance of the NN drops drastically, for example when predicting the friction in scene 1). However, in a more expressive scene with regard to friction, i.e. scene 3), we find comparable performance. From Fig. 5, we also find that the image-space MSE has a favorable shape for the elasticity in the three circle scene, which is reflected in the superior performance when predicting elasticity.

We also investigate the question whether the network can handle scene observations of different nature than the sharp segmentations provided by the simulator. For this purpose, we apply a gaussian filter with $\sigma = 3$ pixels to the observations, so that we obtain a more fuzzy observation. The simulated scenes are, however, supplied in their original, sharp version. In our experiments we did not observe significant changes in the performance of the neural network as a correction estimator.

### B. Bouncing Balls

The second scenario investigates the role of a variable number of objects in the scene. We use the well-known "bouncing balls" scene (a two-dimensional representation of a "pool table"), see Fig. 3d. We place one test object with fixed mass on a pool table that is bounded by four rigid lines. The test mass is accelerated towards a variable number of balls with unknown mass that are placed in a triangular pattern, such that all balls collide with at least one other object. We predict each objects mass separately by marking it with a different color. We randomly place between two and six balls with random mass on the table. To evaluate the performance of our approach, we update each objects mass as predicted by the network and then iterate over the updated guesses. Even in this more complex state space, we find only slightly reduced accuracy after several iterations. However, in comparison to fewer objects, it takes about three to four iterations for the values to converge. We furthermore find that the network is able to predict a scene with just one unknown object with high accuracy, although this setup was not part of the training process, see Fig. 7a, green line.

### V. Limitations

Our method makes several assumptions, which will be discussed here. For instance, the system is currently limited to 2D scenes, but this is not an inherent constraint. Furthermore, we assume that the observed state can be easily compared to the simulated one, in our case by rendering a similar view from the simulation data. As (visual) scene complexity increases, this assumption may not hold anymore.
Fig. 7. Minimum normalized Mean Squared Error between predicted and true parameters for different scene and parameter combinations: a) mass, b) elasticity & friction, c) mass & elasticity. d) shows a comparison between hyperopt and the learned network for mass and mass & elasticity. Note that we show the best parameters until each iteration, with the image-space MSE used to determine the so-far-found optimum.

VI. CONCLUSION

In conclusion, we find that our approach of predicting physical object properties from video allows for much more rapid refinement of parameters in comparison to generic gradient-free parameter optimization techniques. This allows for a fast determination of physical parameters from a video input. The accuracy on all parameters is 10% or better. For higher accuracy, it may be necessary to either finetune the used neural network, or use a generic optimization approach or a differentiable physics engine as a second step in the optimization process. Due to the iterative nature and fast convergence of our approach, it allows for online refinement of physical parameters. In any case, the accuracy of the estimation strongly depends on the expressiveness of the scene with regard to the investigated parameters.

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