**High Performance Computing for Bridging the Sim2Real Gap using Autonomy Oriented Digital Twins: A Survey**

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# Introduction

Simulation-based design and verification offers various benefits such as cost-effective space (in terms of monetary, safety, spatial, temporal constraints) for prototyping/testing [1], controlled settings for variability testing [2-3], control over test case generation and execution, comprehensive corner-case analysis [4-6], safety-critical testing with social and situational variability, rapid evaluation of alternate design choices [7-9], holistic mechatronic design optimization, simulation-as-a-service (SAAS) [10-12], parallel training/testing workloads for faster execution.

However, all these benefits are rendered moot due to the sim2sim [13] and sim2real gap [14-17]. In essence, non-repeatability within same simulation tool and non-uniformity across different simulation tools (sim2sim gap) as well as unmodeled/mismatched dynamics and perception interfaces for real and virtual worlds (sim2real gap) ultimately questions the trustworthiness of simulation-based design and verification.

High performance computing plays a crucial role in bridging the sim2real gap using autonomy-oriented digital twins. Autonomy-oriented digital twins aim to replicate real-world systems and environments in a virtual simulation, allowing for testing and development of autonomous systems without the need for physical prototypes. However, there is often a significant gap between the simulated environment and the real-world conditions, which can limit the effectiveness and applicability of the digital twin.

# Literature Survey

This survey is primarily categorized based on the method adopted for sim2real transfer, while also highlighting the dynamics/perception interfaces.

* **Independent Sim2Real Frameworks:** These include techniques that have to be applied pre/post-development of the autonomy algorithms.
* **Integrated Sim2Real Frameworks:** These include techniques, which can be applied on-the-fly while designing/training the autonomy algorithms.

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| *(a) Literature survey overlay and basis of classification.* | *(b) Overlaps of techniques to break the barriers of sim2real transfer.* |

One approach to bridging this gap is through system **identification**. This method involves calibrating the simulator against real-world system under test (SUT) through varying grades of parameter/system identification. More recently, the concept of differentiable simulation shows promise to update simulation parameters through gradient-based optimization.

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| **Article/Author** | **Category** | **Dataset/Simulator** | **Implemented Tasks** | **Description** | **Interface** |
| **Tan et al. [18]** | Parameter identification | PyBullet | Learning quadruped locomotion | Narrow reality gap by improving the simulator physics and learning robust policies. | Dynamics |
| **Kaspar et al. [19]** | Parameter identification | PyBullet | RL for peg-in-hole task using KUKA LBR iiwa | Perform system identification prior to learning for aligning the simulation environment as far as possible with the dynamics of real robot. | Dynamics |
| **Mehta et al. [20]** | Parameter identification | MuJoCo | Several tasks like pushing a block to goal, sliding a puck to goal, picking and placing a block onto another, moving a ball to goal with hand, opening a door with hand, as well as simple and difficult locomotion of half-cheetah and a humanoid | Use various methods like linear regression (LR), Bayesian optimization (BayesOpt), model-agnostic meta-learning (MAML), simulation parameter distribution optimization (SimOpt) and active domain randomization (ADR) for calibrating robotic simulators. | Dynamics |
| **Sontakke et al. [21]** | Parameter identification | MuJoCo | Walking and turning policies for buoyancy assisted legged robots | Model the nonlinear dynamics of the actuators by collecting hardware data and optimizing the simulation parameters. | Dynamics |
| **Lee et al. [22]** | Parameter identification | Custom | Simultaneous identification of intrinsic and extrinsic parameters of a laser-vision sensor | Use particle swarm optimization (PSO) for sensor model parameter estimation. | Perception |
| **Krishna et al. [23]** | Differentiable simulation | gradSim | Motion of rigid and soft body objects upon impulse input | Identification of a variety of physical parameters such as mass, friction and elasticity of rigid and soft body objects using gradient-based optimization for minimizing variation between true and estimated image/video observations. | Dynamics |
| **Le Lidec et al. [24]** | Differentiable simulation | Custom | Sliding motion as well as elastic collision of rigid body cubes | Identification of a physical parameters such as object mass, coefficient of kinetic friction and coefficient of restitution of rigid bodies using gradient-based optimization for minimizing variation between true and estimated object trajectories. | Dynamics |
| **Heiden et al. [25]** | Differentiable simulation | DiSECt | Cutting of natural soft materials such as fruits (apple) and vegetables (potato) using knife blade | Identification of simulation parameters such as vertical knife velocity, cut spring softness, cut spring stiffness, contact stiffness, contact friction and contact damping using gradient-based optimization for minimizing variation between true and estimated knife blade force. | Dynamics |

Another approach to bridging this gap is through various **adaption techniques**. This involves adapting the simulation domain to match real-world data distribution using certain pre/post-processing methods such as transfer learning, curriculum learning, meta learning, knowledge distillation or imitation learning.

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| **Article/Author** | **Category** | **Dataset/Simulator** | **Implemented Tasks** | **Description** | **Interface** |
| **Kim et al. [26]** | Transfer learning | Kinect | End-to-end autonomous driving with lane semantic segmentation | A continuous end-to-end transfer learning approach which uses two transfer learning steps. | Perception |
| **Akhauri et al. [27]** | Transfer learning | Unity, deepDrive | Autonomous driving domain transfer | Adding the idea of robust RL to transfer learning, learning both parameters and strategies, and transferring the correspondence between the two to the execution environment. | Perception |
| **Wu et al. [28]** | Transfer learning | Blender (BlenSor, BlenderProc) | Automated disassembly of different variants of actuators in vehicle manufacturing | Pre-train the network model on synthetic data, fine-tune the network model on real-world data, and post-process semantically segmented point-cloud for predicting screw locations and orientations. | Perception |
| **Qiao et al. [29]** | Curriculum  learning | PyBullet | Sequential goal tracking | Map low-fidelity (grid-world) simulation to high-fidelity (physics-based) simulation or real-world, using curriculum learning. | Dynamics |
| **Bae et al. [30]** | Curriculum  learning | Isaac Sim | Construct task-independent trajectories for point-to-point motions of robot manipulator | Sim2Real transfer, augmented by curriculum learning, highlights that the robots behave in the same way in the real world as in the simulation. | Dynamics |
| **Xiao et al. [31]** | Curriculum  learning | Custom | Flying quadrotor through narrow gaps | Curriculum learning for searching dynamically feasible flight trajectories with a sim2real framework that can transfer control commands to a real quadrotor without using real flight data. | Dynamics |
| **Qin et al. [32]** | Curriculum  learning | V-REP (CoppeliaSim) | Gait planning of six-legged robot to adapt to complex terrain | Train a robot to safely arrive to the target point through complex terrains and use curriculum learning to speed up and optimize the training. Verify the reliability of the method in simulation platform and finally transfer the learned model to real robot. | Dynamics |
| **Nagabandi et al. [33]** | Meta learning | MuJoCo | Simulation of dynamical models for online adaptation of real scenarios | An online adaptive learning method for high-capacity dynamic models to address the simulation to reality problem. | Dynamics |
| **Jaafra et al. [34]** | Meta learning | CARLA | Autonomous driving strategy | A meta reinforcement learning approach to embedding adaptive neural network controllers on top of adaptive meta-learning. | Both |
| **Kar et al. [35]** | Meta learning | KITTI | Autonomous driving scene generation and rendering | Meta-Sim environment, where images and their corresponding realistic ground images are acquired through a graphics engine. | Perception |
| **Arndt et al. [36]** | Meta learning | MuJoCo | Hitting a hockey puck to a target using robot manipulator (KUKA LBR 4+) | Use meta learning to train a policy that can adapt to a variety of dynamic conditions and use a task-specific trajectory generation model to provide an action space that facilitates quick exploration. | Dynamics |
| **Saputra et al. [37]** | Knowledge  distillation | KITTI, Malaga | Autonomous driving trajectory prediction | Learning teacher's intermediate representations through attentional imitation loss and attentional cue training methods. | Perception |
| **Zhang et al. [38]** | Knowledge  distillation | KITTI, nuScenes | Point cloud map feature extraction | A knowledge distillation method based on point cloud map. | Perception |
| **Sautier et al. [39]** | Knowledge  distillation | SemanticKITTI, nuScenes | 3D image generation for multimodal autonomous driving | A self-supervised knowledge distillation method. | Perception |
| **Li et al. [40]** | Knowledge  distillation | SemanticKITTI, nuScenes | Semantic segmentation of autonomous driving radar data | Transformer-based voxel feature encoder for robust LIDAR semantic segmentation in autonomous driving. | Perception |
| **Zhu et al. [41]** | Imitation learning | MuJoCo | Robotic manipulation for a wide variety of visuomotor tasks | Model-free deep reinforcement learning method that leverages a small amount of demonstration data to assist a reinforcement learning agent. | Both |
| **Desai et al. [42]** | Imitation learning | OpenAI Gym | Experiments in several domains with mismatched dynamics | Generative adversarial reinforced action transformation (GARAT) for grounded transfer learning. | Dynamics |
| **Javed et al. [43]** | Imitation learning | OpenAI Gym | Robotic fabric manipulation task | Novel policy gradient-style robust optimization approach, PG-BROIL, that optimizes a soft-robust objective that balances expected performance and risk. | Both |
| **Tsinganos et al. [44]** | Imitation learning | DART | Multi-stage, multi-object manipulation tasks | Two pipelines for learning a robust robot policy with sim2real: (a) imitation of solution sketches (states alone); and (b) imitation from voxel-based scene representation; and transferring of it in the physical environment. | Both |

Yet another way of bridging the sim2real gap is using **augmentation methods**, which expand the simulation domain to “hopefully” match the real-world data distribution. This includes techniques such as robust reinforcement learning, domain randomization as well as style transfer.

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| **Article/Author** | **Category** | **Dataset/Simulator** | **Implemented Tasks** | **Description** | **Interface** |
| **Malmir et al. [45]** | Robust  reinforcement  learning | DART | Robotic reaching task | Disturbance-augmented Markov decision process in delayed settings to incorporate disturbance estimation in training on-policy reinforcement learning algorithms. | Dynamics |
| **Kim et al. [46]** | Robust  reinforcement  learning | Custom | Control of a simple pendulum | Handling parametric uncertainty and/or input disturbance of simulated vs. real plants by utilizing disturbance observer (DOB). | Dynamics |
| **Josifovski et al. [47]** | Robust  reinforcement  learning | Unity | Robotic reach-and-balance manipulator task | Analyze the effect of randomization: more randomization helps in sim2real transfer, yet it can also harm the ability of the algorithm to find a good policy in simulation. | Dynamics |
| **Yue et al. [48]** | Domain randomization | GTA | Semantic segmentation of autonomous driving scenarios | A new method of domain randomization and pyramid consistency is proposed to learn models with high generalization ability. | Perception |
| **Kontes et al. [49]** | Domain randomization | CARLA | ADAS obstacle-avoidance | More complex road and high-speed traffic situations are considered, and the sim2real transformation is accomplished by training several variants of the complex problem using domain randomization. | Both |
| **Pouyanfar et al. [50]** | Domain randomization | Unity, KITTI | ADAS obstacle-avoidance | Static domain randomization uses real data to solve the end-to-end collision-free depth drive problem. | Perception |
| **Zhang et al. [51]** | Style transfer | Gazebo, CARLA | Visual navigation in indoor and outdoor scenarios | Generative adversarial network (GAN) with cyclic loss, semantic loss as well as shift loss for consistent style transfer. | Perception |
| **Zhang et al. [52]** | Style transfer | Cruise Morpheus Simulator | Mimic the real images as closely as possible in simulation | Utilize “approximately-paired” data that shares contextual information like camera pose, map location, scene composition and lighting, while allowing some variations in assets, textures, appearance and shapes. | Perception |
| **Tripathy et al. [53]** | Style transfer | Cityscapes, Google Maps | Map input label maps to realistic images (and vice versa) for driving scenes and aerial maps | General purpose image-to-image translation model that can utilize both paired and unpaired training data simultaneously. | Perception |
| **Bewley et al. [54]** | Style transfer | Custom (procedural generation) | Visually-aided lane-following autonomous driving | Learning to translate between simulated and real-world imagery, while jointly learning a control policy from this common latent space using labels from an expert driver in simulation. | Both |

Finally, digital twins have a great potential of applying any or all of the aforementioned techniques before/after/while developing the autonomy algorithms and behaviors.

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| **Article/Author** | **Category** | **Dataset/Simulator** | **Implemented Tasks** | **Description** | **Interface** |
| **Xiong et al. [55]** | Identification + augmentation | Unity | Autonomous vehicle in a manned vehicle following scenario with V2V communication | A new digital twin framework of autonomous vehicles consisting of physical entity components, virtual simulation components, and simulation evaluation components is proposed. | Dynamics |
| **Voogd et al. [56]** | Augmentation  +  adaptation | Simcenter Prescan, Simcenter Amesim | Autonomous vehicle in a manned vehicle following scenario with V2V communication | Combining virtual and real-world data to train a path following DRL agent for an autonomous electric vehicle. | Dynamics |
| **Allamaa et al. [57]** | Augmentation +  adaptation | Simcenter Amesim | Nonlinear model predictive control for autonomous vehicle | A new method combining adaptation and augmentation in an online setting for optimizing a nonlinear model predictive control framework for autonomous vehicles saving tedious time and labor consuming tuning. | Dynamics |

In addition to these approaches, there are advancements in information and communication technologies (ICT) that play a crucial role in implementing service-oriented digital twins. Groshev et al. [58] highlight the importance of ICT advancements such as edge computing, network function virtualization (NFV), and 5G in satisfying the required key performance indicators (KPIs) of latency, reliability, bandwidth, and more. These technologies enable the efficient and reliable operation of digital twins, enhancing their performance and applicability.

Furthermore, Lu et al. [59] propose the use of low-latency federated learning and blockchain for edge association in digital twin empowered 6G networks. This approach leverages the power of edge computing and blockchain technology to enable efficient and secure collaboration between digital twins in a distributed network. By reducing latency and ensuring data integrity, this approach enhances the performance and reliability of digital twins in complex control algorithms and mental models.

# Conclusion

In summary, high-performance computing plays a crucial role in bridging the sim2real gap in autonomy-oriented digital twins. Techniques such as identification, adaptation, augmentation and digital twinning enable the transfer of control and behavior from simulation to the real world. Advancements in information and communication technologies, such as edge computing and network function virtualization, enhance the performance and reliability of digital twins. Additionally, low-latency federated learning and blockchain technology enable efficient collaboration between digital twins in distributed networks. These advancements in high performance computing contribute to the development and application of autonomy-oriented digital twins.

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