SIMULATION TO REALITY TRANSFER IN ROBOTIC LEARNING

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ROBOTICS AT NVIDIA

Photos courtesy Dieter Fox and others
OUR MISSION

Drive breakthrough robotics research and development

Enable the next-generation of robots that safely work alongside humans, transforming industries such as
- manufacturing,
- logistics,
- healthcare,
- and more
Navigation for fulfillment, delivery, assembly
Applications focus on
• getting from A to B without collision
• following specific trajectory
HOW DO WE GET

FROM

Better perception?
Tactile sensing?
Cheaper H/W?

TO

Compliant motion?
Planning algorithms?

Natural user interfaces?
End-to-end learning?
Dexterous hands?
DEEP LEARNING REVOLUTION

Already happening

Fast compute

Big data

Where are we?

Variations on theme

Advanced algorithms
VISION DATASETS

- **ImageNet**: 14M images, 1M bounding boxes
- **CIFAR**: 120k images
- **COCO**: 200k images
- **Pascal 3D+**: 30k images
- **Pascal 3D+**: 30k images
- **ObjectNet3D**: 90k images
- **RBO**: 90k images
- **T-LESS**: 50k images
- **FlyingThings3D**: 20k images
- **Sintel**: 50k images

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[ImageNet examples]

[Sample images from ImageNet]

[Sample images from CIFAR]

[Sample images from COCO]

[Sample images from Pascal 3D+]

[Sample images from ObjectNet3D]

[Sample images from RBO]

[Sample images from T-LESS]

[Sample images from FlyingThings3D]

[Sample images from Sintel]
ROBOTICS DATASETS

- KITTI
- iCubWorld
- MPII Cooking
- Robobarista 1k demonstrations
- USF Manipulation 2k trials

- ScanNet
- RoboTurk 2k demonstrations
- UNIPI Hand 114 grasps

- Penn Haptic Texture Toolkit 100 models
- MIT Push 1M datapoints
SIMULATED ACTIONABLE ENVIRONMENTS

Arcade Learning Environment
Gibson
AI2-THOR
AirSim

OpenAI Gym
Roboschool
SURREAL
SIMULATION

Will simulation be **the key** that unlocks robot potential?

Three possibilities:

1. Simulation will *never be good enough* to be used
   “Software simulations are doomed to succeed.” — Rod Brooks

2. Without simulation, interesting robotics problems *cannot be* solved

3. Eventually, simulation will mature to the point where
   1. Robotics will *benefit* from it (accelerate training, validate solutions, etc.)
   2. Some problems may *require* it due to their complexity

*Simulation generates massive data with high consistency*
AN ANALOGY

Then
(Leslie Jones Collection/Boston Public Library)

Now
(Public domain)
AN ANALOGY

Design

Training

Support

(Photo by SuperJet International. CC BY-SA 2.0)

(Photo by Prana Fistianduta. CC BY-SA 3.0)

(Photo by Marian Lockhart / Boeing)
DEMOCRATIZATION
PROBLEM STATEMENT

Environment

Photorealistic

Agent

Physically realistic

Observations

Actions

Simulation

Train

Reality

Apply

$\pi : o \rightarrow a$
LONG WAY TO GO

Today’s robot simulators:
- Not photorealistic
- Not physically realistic

Early flight simulator 1983
Early robot simulator 2017 [Tobin et al. 2017]
BUT PROGRESSING FAST

Photorealism
RTX ray tracing

Physical realism
PhysX 4.0
REALITY GAP

**Reality gap** - discrepancy between simulated data and real data

Three ways to bridge reality gap:

1. Increase fidelity of simulator
   1. *Photo-realism* (light, color, texture, material, scattering, ...; also tactile sensors, ...)
   2. *Physical realism* (dimensions, forces, friction, collisions, ...)

2. Learn mapping to bridge the gap
   Domain adaptation

3. Make controller robust to imperfections
   Domain randomization, add noise during training, stochastic policy

[Dundar et al., 2018]
SIM-TO-REAL SUCCESS

Locomotion

Grasping / Manipulation

Quadrotor flight

[Tan et al., 2018]

[James et al., 2017; Matas et al., 2018]

[Molchanov et al. 2019]

[Hwangbo et al., 2019; Lee et al., 2019]

[Bousmalis et al., 2018]

[Sadeghi et al. 2017]
SIM-TO-REAL AT NVIDIA

Navigation

Manipulation

Vision

Closed-loop control
SIM-TO-REAL AT NVIDIA

Navigation

Manipulation

Vision

Closed-loop control
Domain randomization - Generate non-realistic randomized images

Idea - If enough variation is seen at training time, then real world will just look like another variation

Randomize:

• Object pose
• Lighting / shadows
• Textures
• Distractors
• Background
STRUCTURED DOMAIN RANDOMIZATION (SDR)

**SDR** - Generate randomized images with variety (as in DR) but with realistic structure

Structured Domain Randomization: Bridging the Reality Gap by Context-Aware Synthetic Data
A. Prakash, S. Boochoon, M. Brophy, D. Acuna, E. Cameracci, G. State, O. Shapira, S. Birchfield. ICRA 2019
Not photorealistic, but structurally realistic
**SDR RESULTS**

*Reality gap* is large

*Domain gap* between real datasets is also large

*SDR* 25k outperforms:

- *DR* 25k (synthetic)
- *Sim 200k* (photorealistic synthetic)
- *VKITTI 21k* (photorealistic synthetic with same content)
- *BDD100K* (real)
Network has never seen a real image!
SIM-TO-REAL AT NVIDIA

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Closed-loop control
SIM-TO-REAL AT NVIDIA

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DRIVE SIM AND CONSTELLATION

DRIVE Sim creates the virtual world

DRIVE Constellation runs simulation
SIM-TO-REAL AT NVIDIA

Navigation

Manipulation

Vision

Closed-loop control
SIM-TO-REAL AT NVIDIA

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Manipulation

Vision

Closed-loop control
LEARNING HUMAN-READABLE PLANS

“Place the car on yellow.”

Synthetically Trained Neural Networks for Learning Human-Readable Plans from Real-World Demonstrations
J. Tremblay, T. To, A. Molchanov, S. Tyree, J. Kautz, S. Birchfield. ICRA 2018
DETECTING HOUSEHOLD OBJECTS

Does the technique generalize?

YCB objects [Calli et al. 2015]; subset of 21 used by PoseCNN [Xiang et al. 2018]

Baxter gripper
• parallel jaw
• 4 cm travel dist.
Design goals:
1. Single RGB image
2. Multiple instances of each object type
3. Full 6-DoF pose
4. Robust to pose, lighting conditions, camera intrinsics

DEEP OBJECT POSE ESTIMATION (DOPE)

https://github.com/NVlabs/Deep_Object_Pose
NDDS DATA SET SYNTHESIZER

- Data exporter using UE4
- Near photorealistic
- Domain randomization tool set
- Tutorial and documentation
- Export:
  • 2D bounding box
  • 3D pose
  • Keypoint location
  • Segmentation
  • Depth

https://github.com/NVIDIA/Dataset_Synthesizer
MIXING DR + PHOTOREALISTIC

Together, these bridge the reality gap
 Accuracy needed by our gripper

Accuracy measured by area under the curve
### RESULTS ON YCB-VIDEO

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<th></th>
<th>Cracker</th>
<th>Sugar</th>
<th>Soup</th>
<th>Mustard</th>
<th>Meat</th>
<th>Mean</th>
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<tr>
<td>DR</td>
<td>10.37</td>
<td>63.22</td>
<td>70.20</td>
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<td>23.16</td>
<td>6.23</td>
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<td>65.07</td>
</tr>
</tbody>
</table>

Area under the curve for average distance threshold

**DOPE trained only on synthetic data outperforms leading network trained on syn + real data**
DOPE IN THE WILD

PoseCNN

DOPE (ours)
SIM-TO-REAL AT NVIDIA

Navigation

Manipulation

Vision

Closed-loop control
SIM-TO-REAL AT NVIDIA

Navigation

Manipulation

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Closed-loop control
TRADITIONAL APPROACH

Input: Pose Estimation

Open-Loop

Inverse Kinematics + Motion Planning

Result:
DOPE FOR ROBOTIC MANIPULATION

Hand camera not used
DOPE ERRORS
CLOSED-LOOP GRASPING

Feedback loop corrects errors in estimation / calibration

ARCHITECTURE

Trained via DDQN
(double deep Q-network)
SIMULATED ROBOT FARM
SIMULATED ROBOT FARM

Policy is trained entirely in simulation
RESULTS

Closed loop policy grasping object
LEARNING INVERSE DYNAMICS

Simulation

Reality

Videos courtesy David Hoeller
REAL-TO-SIM

Video courtesy David Hoeller
SIM-TO-REAL AT NVIDIA

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Manipulation

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Closed-loop control
SIM-TO-REAL AT NVIDIA

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BAYES SIM

Training learns distribution of parameters

After training

BayesSim: Adaptive domain randomization via probabilistic inference for robotics simulators

F. Ramos, R. C. Possas, D. Fox. Under review, 2019
CLOSING THE SIM-TO-REAL LOOP

Swing-peg-in-hole
Simulated environment
CLOSING THE SIM-TO-REAL LOOP

Swing-peg-in-hole
Simulated environment

Swing-peg-in-hole
Real robot: SimOpt Iteration 0

Closing the Sim-to-Real Loop: Adapting Simulation Randomization with Real World Experience
CLOSING THE SIM-TO-REAL LOOP

Simulation

Reality
SIM-TO-REAL LANDSCAPE

- large-scale grasping
- mobile manipulation
- machine tending
- in-hand manipulation
- tactile sensing
- object state changes
- non-rigid objects
- liquids
- fast movement
- generalization

...
CONCLUSION

Simulation will be key for robotics in

- Generating large amounts of labeled training data
- Quantitatively verifying policies / algorithms

Photorealism and physical realism are almost here

Many open problems:

- Tactile sensors?
- Authoring content?
- Model verification?
- Super-real-time training?
- Soft contact modeling?
- Scaling?
- Adaptation?
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Vijay Baiyya
Jeffrey Smith
Johnny Costello
and many others

https://github.com/NVIDIA/Dataset_Synthesizer
https://github.com/NVlabs/Deep_Object_Pose