Robotics Standards and Performance Measurement



nerve.uml.edu







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ASTM International Board of Directors, Director (2024-2026 term)

ASTM F45 Committee Chair

ASTM F48 Standards development, Voting member

ASTM E54.09 Standards development, Voting member

ARM Institute Metrics and Evaluation Working Group, Lead

COMPARE Ecosystem, Community Facilitator

IEEE RAS TC for Performance Evaluation & Benchmarking of Robotic and Automation Systems (PEBRAS), Co-Chair

Robotics research interests: test methods, performance evaluation, metrics, benchmarking, reproducibility, and standardization







University of Massachusetts Lowell

New England Robotics Validation and Experimentation (NERVE) Center

Interdisciplinary robotics testing, research, and training facility that evaluates robot capabilities, human performance, and human-robot interaction







Exoskeletons and Wearable Robots



Human Performance



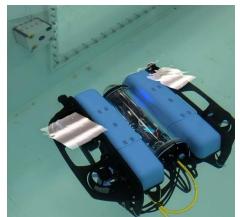
Legged Robots Systems



Human-Robot Teaming







Aquatic Robot Systems



Uncrewed Ground Vehicles



Grasping and Manipulation







Benchmarking

Standards

Reproducibility

Evaluation

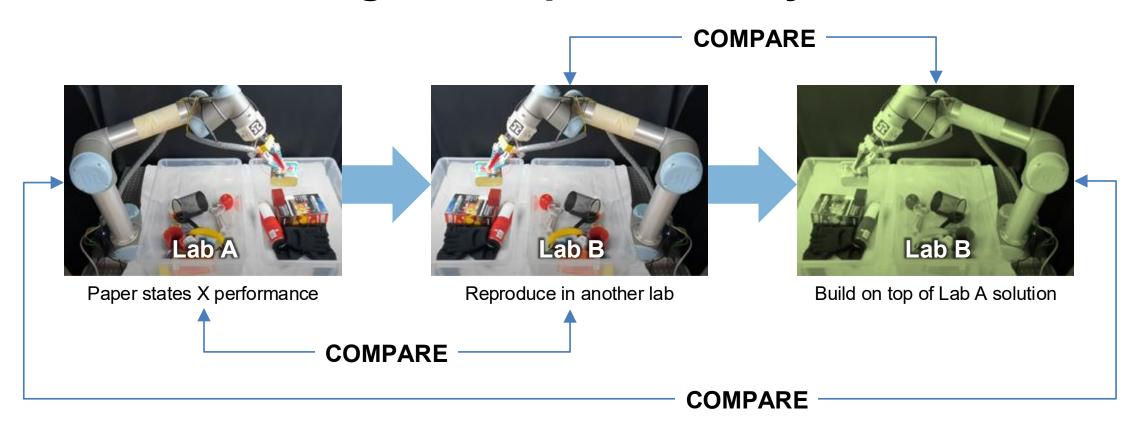
Generalizability







Benchmarking and Reproducibility in Robotics



What can be reproduced?

Context → Functionality → Results

What can enable reproducibility?

Open-Source | Standards



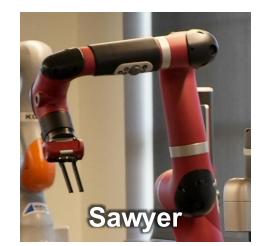




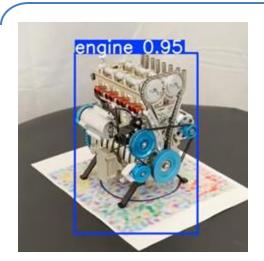
robot-manipulation.org

Benchmarking Robot Manipulation

HARDWARE







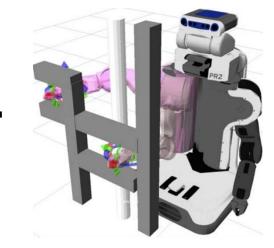
Perception



SOFTWARE

Grasp Planning

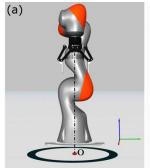




Motion Planning

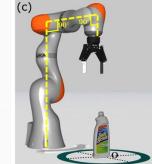
[Ten Pas et al., 2017]

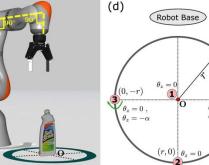
EVALUATION

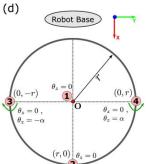




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METRICS _____

Trial #	Object name (YCB ID)	Pickup order	Selected (total Feasible)	Time (seconds)	Lift Test	Rotational Test	Shaking Test
1	Yellow Cup (56)	4	19 (100)	2.874	~	~	~
	Racquete ball (53)	2	6 (60)	6.083	~	~	~
	Scrub Cleanser (20)	3	7 (69)	6.665	~	~	~
	Flat Screwdriver (43)	6	1 (10)	0.229	~	~	~
	Big Clamp (46)	5	21 (100)	2.36	V	~	~
	Toy plane (67)	1	1 (82)	5.891	~	~	~
2	Yellow Cup (56)	2	54 (100)	6.121	~	~	~
	Racquete ball (53)	3	65 (73)	5.185	~	~	~
	Scrub Cleanser (20)	4	51 (52)	5.106	~	~	~
	Flat Screwdriver (43)	6	1 (90)	1.073	~	~	~
	Big Clamp (46)	5	63 (87)	4.36	~	~	~
	Toy plane (67)	1	54 (100)	6.424	~	~	~

Benchmarking Protocol

[Bekiroglu et al., 2020]





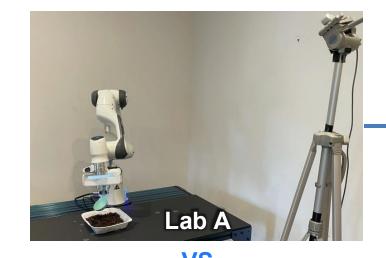


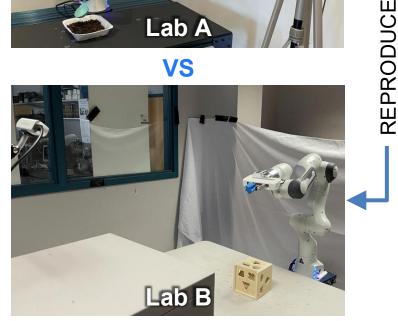


RB2: Robotic Manipulation Benchmarking with a Twist

[Dasari et al., 2022]

- Compared five learning approaches run "identically" in two different labs to perform pouring, scooping, insertion, and zipping tasks
- ~20% variation in performance results observed when reproducing the experiments across the two labs
- "...building precisely reproducible robotic setups is impossible and therefore absolute performance numbers on a benchmark task are meaningless..."







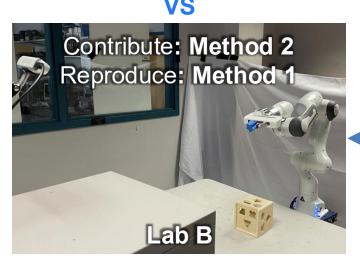




RB2: Robotic Manipulation Benchmarking with a Twist [Dasari et al., 2022]

- Local relative ranking (LRR): each lab establishes a baseline in their lab for comparison by reproducing the contribution of the other lab and running experiments
- Developed for the evaluation of software/algorithms as they can be easily shared (as opposed to hardware)
- The authors also propose a method to globally rank the contributed LRRs from multiple labs (see paper)











REPRODUCE

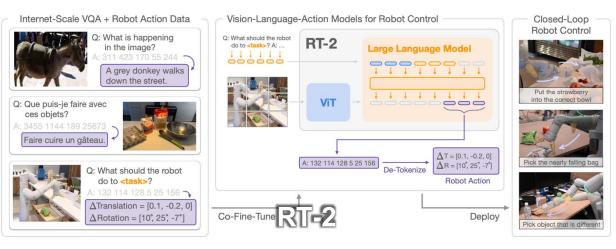
Benchmarking Robot Manipulation

HARDWARE



Robot

SOFTWARE



[Zitkovich et al., 2023]

Vision-Language-Action Model (VLA)

(a) Unseen Objects (b) Unseen Backgrounds (c) Unseen Environments (b) Unseen Environments (c) Unseen Environments (d) Unseen Environments (e) Unseen Environments (first stocerrect; Ideal and units of pilat of the ball of the stocerrect; Ideal and units of the stocer Ideal a

METRICS

100%

75%

50%

25%

O%

Seen Tasks

Unseen
Objects

Backgrounds Environments

Average

Benchmarking Protocol

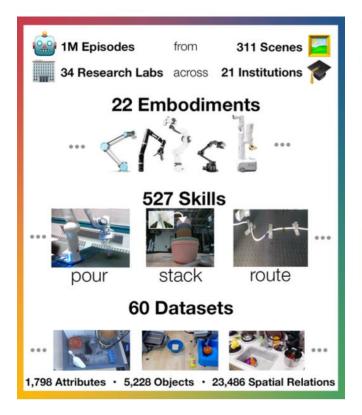
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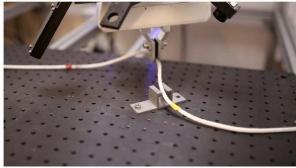
[Zitkovich et al., 2023]















At UC Berkeley (RAIL)

At University of Freiburg (AiS)

At NYU (CILVR)







At UC Berkeley (AUTOLab)

At Stanford (IRIS)

At USC (CLVR)

Cross-embodiment training results in generalist models that outperform specialist models on their own tasks

Open X-Embodiment [O'Neill et al., 2024] https://robotics-transformer-x.github.io/







- Sergey Levine, "Benchmarks, Surrogate Objectives, and Cross-Embodiment," RSS 2025 Workshop on Benchmarking Robot Manipulation: Improving Interoperability and Modularity
 - Shared benchmarks can be very challenging, so benchmarks are essentially "surrogate functions" (very local surrogate functions)
 - Benchmarks are local!

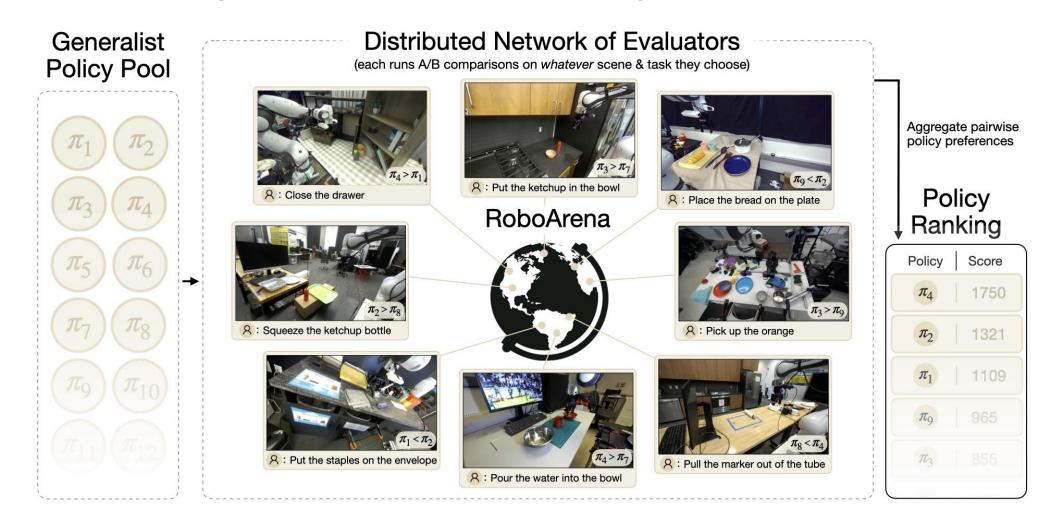
 Benchmarks are local!

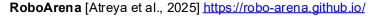
 mpossible and therefore absolute performance numbers on a benchmark task are meaningless..."
 - To be practical, researchers should be able to run their own evaluations
 - Require more honesty and transparency from researchers

















Standard Test Methods Applicable to Humanoids

ASTM E54 Committee on Homeland Security Applications ASTM E45.09 Subcommittee on Response Robots



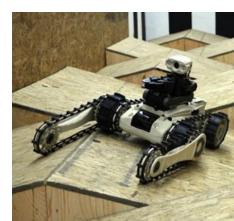






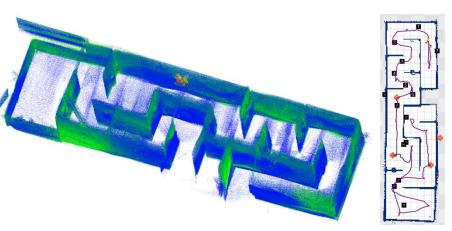












Mobility

Endurance Mapping



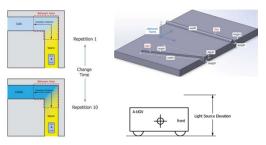




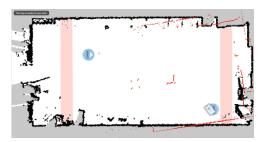
Standard Test Methods Applicable to Humanoids

ASTM F45 Committee on Robotics, Automation, and Autonomous Systems





Environment



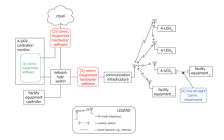
A-UGV Localization



Robotic Grasping



A-UGV Docking



System Communication



Robotic Manipulation



A-UGV Navigation



System Interoperability



Mobile Manipulators



A-UGV Obstacle Avoidance



Robotic End-Effectors



Legged Robots





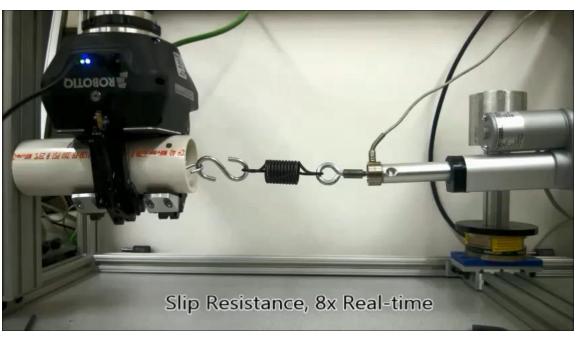


Standard Test Methods Applicable to Humanoids F45.05 Subcommittee on Grasping and Manipulation



Evaluating Grasp-Type End-Effector Grasp Strength and Slip Resistance





ASTM F3756-25 Standard Practice for Grasp-Type Robot End-Effectors: Split Force Measurement Apparatus ASTM WK83863 Grasp-Type Robot End-Effectors: Grasp Strength Performance ASTM WK96472 Standard Test Method for Grasp-Type Robot End-Effectors: Slip Resistance ASTM WK96417 Standard Test Method for Grasp-Type Robot End-Effectors: Cycle Time







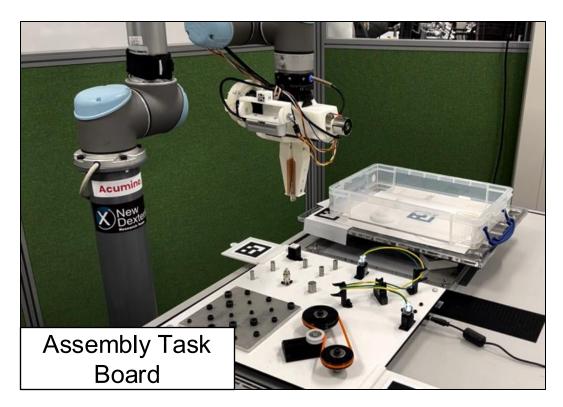




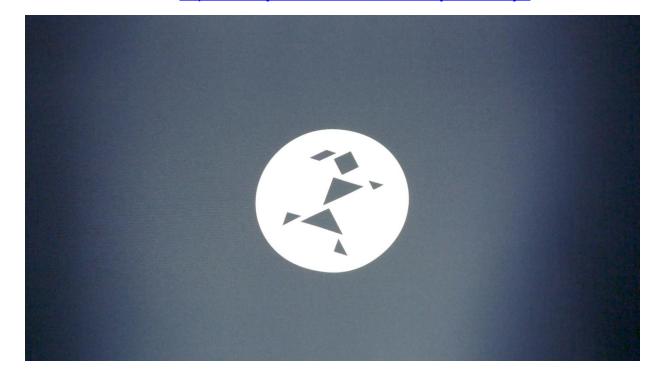
Standard Test Methods Applicable to Humanoids F45.05 Subcommittee on Grasping and Manipulation



Evaluating Robotic Assembly Tasks



Video: https://www.youtube.com/watch?v=Fy8dnS45YyA



ASTM WK87214 Robotic Assembly Task Boards: Benchmarking performance ASTM WK87213 Robotic Assembly Task Boards: Recording Assembly Test Configuration











Standard Test Methods Applicable to Humanoids F45.05 Subcommittee on Grasping and Manipulation



Evaluation of Non-Continuous and Continuous Mobile Manipulator Tasks











ASTM F3713-25 Standard Practice for Measuring Mobile Manipulator Performance: Recording the Workpiece Configuration ASTM WK89198 Mobile Manipulator Performance: Continuous Tasks
ASTM WK83858 Measuring Mobile Manipulator Performance: Non-continuous Tasks
ASTM WK92144 Measuring Mobile Manipulator Performance: Inducing Workpiece Disturbance Impairment











Standard Test Methods Applicable to Humanoids

"The Kick Test" / "The Hockey Stick Test"











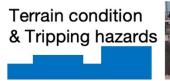
Standard Test Methods Applicable to Humanoids F45.06 Subcommittee on Legged Robot Systems



Disturbance Rejection Testing of Legged Robot Locomotion



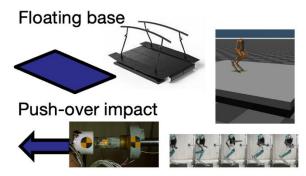
Static Disturbances







DynamicDisturbances



IOWA STATE UNIVERSITY

ASTM WK86916 Test Methods for Disturbance Rejection Testing of Legged Robots







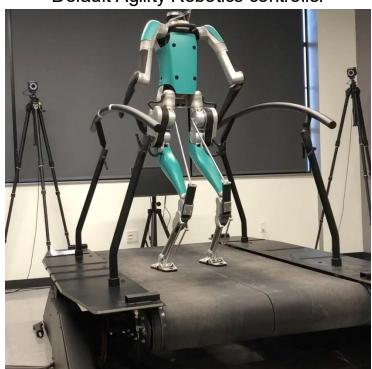


Standard Test Methods Applicable to Humanoids F45.06 Subcommittee on Legged Robot Systems



Disturbance Rejection Testing of Legged Robot Locomotion

Default Agility Robotics controller



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Custom research controller



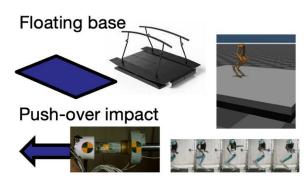
Static Disturbances







DynamicDisturbances



[Gao et al., 2022]

ASTM WK86916 Test Methods for Disturbance Rejection Testing of Legged Robots









Standard Test Methods Applicable to Humanoids

Repeatability: ISO 9283:1998 Manipulating industrial robots — Performance criteria and related test methods



Universal Robots UR5:

+/- 0.1 mm [0.004 in]



IEEE Humanoids Conference 2025, October 2, 2025, Seoul, Korea







Standard Test Methods Applicable to Humanoids

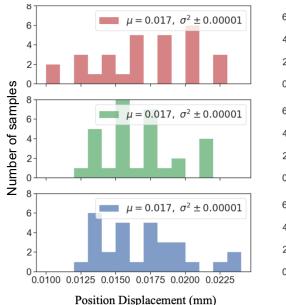
Repeatability: ISO 9283:1998 Manipulating industrial robots — Performance criteria and related test methods

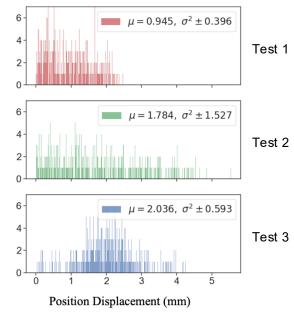
UR10e with commercial algorithm and software stack











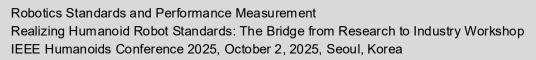
ISO 9283 procedure does not yield consistent and repeatable results for humanoids

[Weng et al., 2025]











Benchmarking

Standards

If benchmarking results in research are local, can they be used for global comparison through standard test methods?

Reproducibility

How can we update the standards we have for humanoid robots that allows them to be trusted and repeatable?

Evaluation

Generalizability







robot-manipulation.org

An online landing page for open-source and benchmarking in robot manipulation, including:





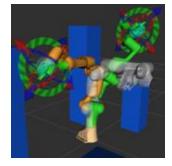
Repositories of open-source products and benchmarking assets





Event listings for workshops, competitions, and webinars

Open-Source Products

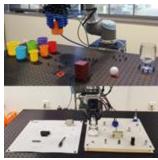


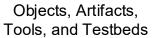




Hardware Designs

Benchmarking Assets







Protocols and Leaderboards

- Repositories and event listings that can be filtered and sorted
- Google Forms available for users to submit content
- Google Calendar of events you can subscribe to
- Updates are communicated over Slack and Google Group









COMPARE Slack (discussion)



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Robotics Standards and Performance Measurement

Thank you!

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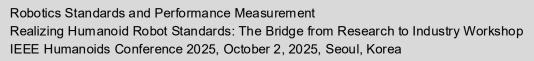






Group (mailing list)







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