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► To cite this version:

Heesun Choi, Cindy Crump, Christian Duriez, Asher Elmquist, Gregory Hager, et al.. On the use of simulation in robotics: Opportunities, challenges, and suggestions for moving forward. Proceedings of the National Academy of Sciences of the United States of America, 2021, 118 (1), 10.1073/pnas.1907856118 . hal-04276447

HAL Id: hal-04276447

<https://inria.hal.science/hal-04276447>

Submitted on 9 Nov 2023

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On the use of simulation in robotics: opportunities, challenges, and suggestions for moving forward

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This manuscript was compiled on May 24, 2020

1 **The last five years marked a surge in interest for and use of smart**
2 **robots, which operate in dynamic and unstructured environments**
3 **and might interact with humans. We posit that well-validated com-**
4 **puter simulation can provide a virtual proving ground that in many**
5 **cases is instrumental in understanding safely, faster, at lower costs,**
6 **and more thoroughly how the robots of the future should be de-**
7 **signed and controlled for safe operation and improved performance.**
8 **Against this backdrop, we discuss how simulation can help in**
9 **robotics, barriers that currently prevent its broad adoption, and po-**
10 **tential steps that can eliminate some of these barriers. The points**
11 **and recommendations made concern the following simulation-in-**
12 **robotics aspects: simulation of the dynamics of the robot; simulation**
13 **of the virtual world; simulation of the sensing of this virtual world;**
14 **simulation of the interaction between the human and the robot; and,**
15 **in less depth, simulation of the communication between robots. This**
16 **perspectives contribution summarizes the points of view that coa-**
17 **lesced during a 2018 National Science Foundation/Department of**
18 **Defense/National Institute for Standards and Technology workshop**
19 **dedicated to the topic of hand. The meeting brought together par-**
20 **ticipants from a range of organizations, disciplines, and application**
21 **fields, with expertise at the intersection of robotics, machine learn-**
22 **ing, and physics-based simulation.**

Robotics | Simulation | Design | Controls | Machine Learning

1 Robots are no longer stiff/rigid implements operating in
2 the structured environment of assembly lines and performing
3 scripted and limited sets of operations. Emerging artificial
4 intelligence techniques will endow the next generation of robots
5 with mobility and decision-making skills. These robots will
6 be flexible, reconfigurable, interact with humans and operate
7 in environments that are unstructured, uncertain and rapidly
8 changing in time. It is expected of them to assume new roles
9 such as operating on highways as autonomous vehicles, in
10 nursing homes assisting social workers, in schools tutoring
11 young learners, underwater managing oil spills, in the adverse
12 and cluttered environments of search-and-rescue missions, or
13 remotely performing surgeries. While physically testing these
14 robots before deployment is mandatory, through simulation,
15 the engineering design process can be accelerated, made more
16 cost effective, and benefit from more thorough testing.

This manuscript is a reflection of ideas, observations and
suggestions that emerged during a one-day workshop on the
topic of using simulation in robotics (1). A word cloud based
on participant input is shown in Fig. 1. This participant input,
in raw form and organized in anonymized decks of slides, is
available online (2). The hope is that this document, which
provides a synthesis of the input contributed by the workshop
participants, becomes a useful reference, resource, and call-to-
arms for colleagues from the simulation community interested
in applying their expertise in the rapidly evolving field of
smart robotics. To that end, this contribution seeks to identify
opportunities, point out challenges, and suggest possible next
steps vis-à-vis the goal of increasing the role that computer
simulation plays in smart robotics.

The manuscript is organized in three parts. The first sum-
marizes benefits that simulation could deliver upon its use
in designing robots over the next decade; i.e., near-term. A
subsequent section points out several hurdles that hinder the
wide use of simulation in practice. Lastly, we identify steps be-
lieved to accelerate the near-term role that simulation plays in
robotics. The intent was to generate a snapshot that captures
this group’s perspective on the potential, hurdles, and path
forward for the simulation-in-robotics idea. This contribution
is not a review of the simulation-in-robotics literature; refer-
ences were used sparingly to point the reader to contributions
that further elaborate on ideas that were only briefly stated in
this manuscript and, where necessary, to provide a historical
perspective on the topic at hand. We purposely maintained a
short reference list, dictated by publication length constraints
and the stated purpose of this manuscript – to provide a “per-
spectives” opinion rather than a review of the state of the
art.

How simulation is, or could be useful in robotics

Ideas embedded in pre-workshop contributions (1) and further
discussions during the joint meeting brought into focus several
simulation opportunities in robotics:

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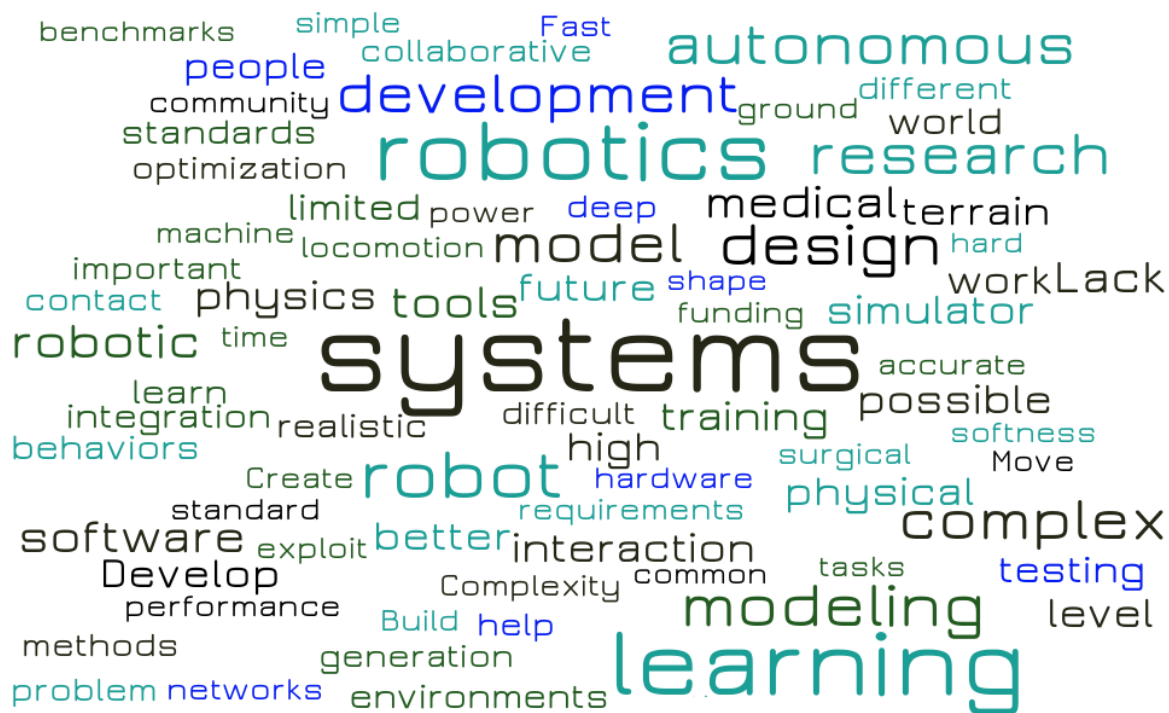


Fig. 1. Word cloud generated using participant-provided pre-workshop input. Word size proportional to use count; "simulation" was excluded.

- 53 1. Generate, expeditiously and at low cost, large amounts
54 of training data for Machine Learning
- 55 2. Accelerate the engineering design cycle; **reduce its costs**
- 56 3. Provide an accelerated, safe, and fully controlled virtual
57 testing and verification environment
- 58 4. **Facilitate the development of more intelligent robots**
- 59 5. Facilitate the understanding of human-robot interactions
60 (HRI)

61 **Opp.1. Generate, expeditiously and at low cost, large**
62 **amounts of training data for Machine Learning.** The
63 recent surge of Machine Learning use in defining control poli-
64 cies (3), and the associated need for a wealth of training data,
65 provided a major impetus to the use of simulation in robotics.
66 A validated simulation platform becomes an ideal proving
67 ground for developing systems that can both learn from their
68 mistakes and be verifiable. Simulation can be used to optimize
69 new behaviors and to carry out tasks never known to be possi-
70 ble. The advantage of using simulation to generate training
71 data becomes even more compelling when the software used
72 can draw on ubiquitous high-throughput computing resources;
73 i.e., using multiple nodes to carry out batches of simulations in
74 parallel and perhaps in the cloud. Using simulation to generate
75 training data for control policies is not a silver bullet owing to
76 the so called simulation-to-reality gap (4), which is touched
77 upon later in the document. Enhancing the transferability
78 attribute of simulation-learned control policies represents an
79 area of active research, see, e.g., (5–7).

80 **Opp.2. Accelerate the engineering design cycle; reduce**
81 **its costs.** There are two time consuming stages in the design
82 of a new robot: the mechanical design and the control policy
83 design. The former is concerned with producing a solution that
84 can execute a predefined set of tasks. The latter is concerned

with endowing the robot with smarts to actually carry out the
tasks that it has the potential to execute. For both mechanical
and control policy design, one typically produces prototypes
that iteratively improve on previous versions until a certain
prototype is acceptable; this prototype becomes a candidate
solution. The iterative process to produce the candidate solu-
tion is time consuming. Additionally, it can be expensive,
unsafe (for humans or the robot hardware) and sometimes
impractical (if designing a rover for Mars, testing cannot be
done in Martian conditions). Moving from a model-free to a
model-based design approach; i.e., carrying out the iterative
loop in simulation (8), can reduce the time associated with the
design process. Indeed, changing a rover suspension design
to assess trafficability in simulation can be as fast as modi-
fying a handful of parameters in a template file that defines
the geometry of the vehicle (9). By comparison, physically
modifying the suspension of a prototype is significantly more
time consuming. Additional time and cost savings are in-
curred in the subsequent stage, the testing of the candidate
design. Before it becomes the solution, the candidate design
is subjected to extensive additional testing in which a limited
collection of candidate design clones are assessed via a pre-
defined evaluation process. Physically building the collection of
candidate designs is time consuming and costly since there
is no assembly line ready yet and each clone is handcrafted.
In simulation, testing the candidate might be as simple as
copying the model files to different folders and conducting the
predefined evaluation process using high throughput, parallel
computing.

Opp.3. Provide an accelerated, safe, and fully con-
trolled virtual testing and verification environment.
Approaches to verification of autonomous systems are in their
infancy (10). Approaches to verification and “debugging”

118 of autonomous robotic systems that learn on-line are essen- 179
119 tially non-existent. Repeatability, particularly with respect 180
120 to stress/corner cases; full control of the experiment insofar 181
121 as the “environment” is concerned; and the lack of risk to 182
122 human and hardware damage are three attributes that can 183
123 make simulation instrumental in establishing principled pro- 184
124 tocols for autonomous system verification and, by extension, 185
125 industry standards and guidelines. Against this backdrop, 186
126 as autonomous systems cannot foresee unknowns that they 187
127 may encounter, novel formal verification schemes can be devel- 188
128 oped to verify specifications such as safety in real-time under 189
129 assumed uncertainty in the system and its environment (11). 190

130 Simulation can play an important role in providing insights 191
131 into multi-robot, collaborative scenarios (12, 13). Collabo- 192
132 rative, multi-robot systems can exclusively comprise robots 193
133 interacting with each other based on their own local decision- 194
134 making algorithms that factor in sensed and/or shared infor- 195
135 mation; or, can include human interaction as in, for instance, 196
136 search and rescue scenarios. As the number of robot-robot 197
137 and/or human-robot interactions increases, so does the com- 198
138 plexity of designing and verifying these systems. Physical 199
139 testing and verification are daunting as the collection of sce- 200
140 narios to probe increases quadratically with the number of 201
141 agents in the system. Moreover, it is difficult to systematically 202
142 test in real conditions multi-robot systems used, for instance, 203
143 in environmental monitoring, off-road mobility/survivability, 204
144 surveillance or infrastructure management, etc., due in part to 205
145 the stiff challenges posed by operating groups of agents in such 206
146 environments. Simulation is very convenient in such scenarios, 207
147 given that it can also be used to probe for inter-agent connectiv- 208
148 ity failure or hostile network penetration. **Hostile/adversarial 209**
149 **attacks aim at more than multi-robot network penetration – 210**
150 **the robot’s control stack and sensing system are two other 211**
151 **targets (14). One of the most compelling cases for use of 212**
152 **simulation in robotics can be made in conjunction with the 213**
153 **need to thoroughly check the consequence of such attacks. Do 214**
154 **the checks designed to guard against adversarial attacks work 215**
155 **as expected? What is a safe way to counteract an adversarial 216**
156 **attack? The answer to these and similar questions is critical 217**
157 **for safety and regulatory purposes yet direct hardware testing 218**
158 **is costly and potentially unsafe (bulky robots gone awry can 219**
159 **become outright dangerous). Simulating the response of the 220**
160 **robotic system in cases of failure, while potentially performing 221**
161 **a task, permits the investigation of fail-safe strategies for the 222**
162 **system as well as the design of security, anti-breach policies. 223**
163 **Without simulation, one is limited in what and how many 224**
164 **scenarios can be tested. 225**

165 **Opp.4. Facilitate the development of more intelligent 226**
166 **robots. In this argument, the intelligence metric is tied to 227**
167 **the breadth of scenarios in which the robot is expected to 228**
168 **successfully fulfill a set mission. By this metric, industrial 229**
169 **robots are at one end of the spectrum. They operate in very 230**
170 **structured and static environments (known ahead of time) 231**
171 **and are trained to perform a narrow and a priori established 232**
172 **catalog of operations. The opportunity to develop more intelli- 233**
173 **gent robots is a consequence of several technological advances: 234**
174 **machine learning techniques opened the door to new control 235**
175 **policies (3); the compute speeds available on an affordable 236**
176 **power budget have increased substantially; sensing is sharper 237**
177 **and more affordable; actuation is gradually becoming more so- 238**
178 **phisticated; low latency communication/networking and edge 239**

computing allow for real-time, just-in-time off-loading of heavy- 179
duty computation during operation. Against this backdrop, 180
simulation can be a catalyst for the next stage in the evolution 181
of smart robots, one in which they operate in unstructured 182
environments and engage in decision-making activities. Just 183
as the concepts of morality (set rules), prior experience and 184
ability to predict the consequence of one’s actions shape the 185
decision-making process in humans, a set of rules (includ- 186
ing ethical) and an ability to predict consequences/outcomes 187
through on-line simulation can shape the decision-making pro- 188
cess of robots through introspection (15). A rule that states 189
“plates shall not drop on the floor” combined with the ability to 190
run thousands of parallel simulation scenarios faster than real 191
time should determine the robot to place on a table the plate 192
at the top of the stack that it carries rather than one from 193
somewhere in the middle of the stack. **The ability to foresee 194**
195 **on-line the outcome of a possible action through the lens of 196**
196 **simulation is anchored by spectacular gains in computation 197**
197 **speed. For instance, recent GPU cards can manage the simul- 198**
198 **taneous execution of more than 150,000 computing threads 199**
199 **(16). With simple enough simulation kernels, this translates 200**
200 **into peeking into the future via as many possible scenarios, 201**
201 **leading to introspective control policies that complement the 202**
202 **established model predictive control approach and more recent 203**
203 **techniques that rely on on/off-line machine learning solutions 204**
204 **(17).**

205 **Opp.5. Facilitate the understanding of human-robot 206**
206 **interactions (HRI). The ability to simulate the interaction 207**
207 **between the robot and human opens the door to experimen- 208**
208 **tation with tele-surgical robotics in semi-autonomous or au- 209**
209 **tonomous operation; reducing risks to individuals in dangerous 210**
210 **work environments or working in cooperation with collabora- 211**
211 **tive and mobile robots in a shared workplace; eliminating 212**
212 **or reducing repetitive motion trauma and musculoskeletal 213**
213 **overload; reducing fatalities and injuries from motor vehicle 214**
214 **incidents as autonomous vehicles are yet another form in which 215**
215 **robots interact with humans. The human-robot interplay can 216**
216 **project specialized medical expertise and care to any point 217**
217 **of need, at any time. This is of particular interest for teams 218**
218 **operating remotely, e.g., small teams of first responders, teams 219**
219 **of astronauts, etc. Finally, one important facet of the science 220**
220 **of HRI pertains to the aspect of establishing trust between hu- 221**
221 **man and robot in shared decision-making (18). Development 222**
222 **of simulation tools that better represent the psycho-social 223**
223 **nature of HRI and enable a common operating “picture” of 224**
224 **possible solution sets for decision-making may foster trust and 225**
225 **establish a baseline for more effective collaboration (19).**

226 **Barriers to the use of simulation in robotics**

227 This section summarizes issues that, to various degrees, limit 228
228 the role played by simulation in robotics. A noncomprehensive 229
229 list of open problems vis-à-vis the topic at hand includes the 230
230 following:

- 231 1. **Scarcity of solutions; producing a simulation platform for 232**
232 **robotics requires broad multi-disciplinary expertise and 233**
233 **sustained software development commitment**
- 234 2. **Existing modeling languages are immature at a time when 235**
235 **a robotics simulation ontology is only slowly emerging**
- 236 3. **Model composability needs further improvements**
- 237 4. **Simulation is not fast enough**

- 238 5. Uncertainty is marginally handled
- 239 6. Model calibration can be tedious
- 240 7. Data-driven approaches (surrogate models; replacing sim- 300
- 241 ulation with an oracle) are only slowly emerging 301
- 242 8. Difficulties in gauging the needed level of model complex- 302
- 243 ity 303
- 244 9. Handling the human-robot interaction 304

245 **Issue 1. Scarcity of solutions; producing a simu- 305**
246 **lation platform for robotics requires broad multi- 306**
247 **disciplinary expertise and sustained software devel- 307**
248 **opment commitment.** After an evolution that spanned 308
249 decades, Computer Aided Engineering (CAE); i.e., the use of 309
250 computer simulation in customary engineering, has become 310
251 a linchpin in the design process. For instance, one can carry 311
252 out a highly predictive finite element analysis of an engine 312
253 crank shaft or of an airplane wing to accurately identify vi- 313
254 bration/flutter modes. Likewise, a vehicle ride analysis can 314
255 be performed via a dynamics simulation in which a vehi- 315
256 cle operating on a flat, rigid surface follows a sequence of 316
257 driving maneuvers to collect information for a subsequent 317
258 noise/vibration/harshness analysis. Compared to what a CAE 318
259 simulation looks like today, simulation in robotics is less struc- 319
260 tured and vastly more multi-disciplinary. The “less structured” 320
261 attribute is tied to the observation that a relatively simple 321
262 set of boundary conditions and load functions are enough to 322
263 define the backdrop for a CAE-type analysis. In robotics, the 323
264 backdrop is more complex and uncertain, and thus harder to 324
265 define. For instance, the robot can operate in and interact 325
266 with an unstructured and evolving world; or a human can be 326
267 part of the equation. The “multi-disciplinary” attribute is 327
268 a consequence of the fact that for simulation in robotics, in 328
269 addition to producing models for robot dynamics, which is in 329
270 the purview of CAE, one has to engage in non-CAE tasks, e.g., 330
271 bring in sensor simulation required for agent control; represent 331
272 in high fidelity the unstructured environment surrounding the 332
273 robot (this virtual world might have to be itself simulated 333
274 since its state can be influenced by the robot dynamics, e.g., 334
275 rover changing the world by creating deep ruts that must be 335
276 captured by the camera sensor of a following rover); simulate 336
277 the human dimension in HRI; and, simulate agent-to-agent or 337
278 agent-to-infrastructure communication. These *simulator sub-* 338
279 *components*, which are tied to the dynamics, sensing, virtual 339
280 world, human participation, and communication facets render 340
281 the simulation-in-robotics task highly multi-disciplinary. As 341
282 an example, consider sensor simulation – it alone calls for 342
283 knowledge in several disciplines as robotics applications rely 343
284 on multiple classes of sensors, e.g., GPS, IMU, LiDAR, camera, 344
285 radar, thermal, etc., each drawing on vastly different physics 345
286 for characterizing the sensing paradigms that come into play. 346
287 Finally, one has to integrate these subcomponents and turn the 347
288 sum of the parts into an usable simulation platform, a process 348
289 that adds a software engineering facet to the multi-disciplinary 349
290 nature of the task at hand. 350

291 **Issue 2. Existing modeling languages are immature at 351**
292 **a time when a robotics simulation ontology is only 352**
293 **slowly emerging.** Specifying/defining/setting up a *scenario* 353
294 *model* for simulation in robotics can be daunting. Indeed, one 354
295 has to specify a slew of parameters that define the geometry 355
296 of the robot, its kinematics, loads, actuators, sensor package 356
297 information, the virtual world it operates in (weather, time of 357

day, satellite position, terrain properties, etc.), communication 298
types and protocols, control policy type, etc. The scenario 299
modeling abstractions that are needed should be conducive to 300
yielding models with hierarchical structure that accommodate 301
the user’s requirements vis-à-vis the level of fidelity rendered 302
in simulation – from less accurate but expeditious, to highly de- 303
tailed/accurate but computationally more demanding. Gazebo 304
(20, 21) has made good strides in this direction, continuing in 305
the tradition of previous tools like USARSim (22). However, 306
the ontology associated with Gazebo’s modeling approach and 307
other similar efforts (23) is limited in scope. Dwelling on the 308
Gazebo example, the platform exposes one simulation interface 309
to several engines: ODE (24), Bullet (25), DART (26), and 310
Simbody (27). Presently, the Gazebo simulation-in-robotics 311
ontology does not include concepts such as “fluid viscosity”, 312
“material dissipation model”, “soil plasticity”, “Drucker-Prager 313
yield”, etc. since none of the Gazebo-exposed physics engines 314
supports fluid dynamics, plasticity in soils, finite element an- 315
lysis, etc. There are simulation engines that have started to 316
support multi-physics with various degrees of success (28, 29) 317
yet these engines presently come short on exposing robotics- 318
focused modeling abstractions. In moving forward, lessons can 319
be learned from software platforms used to create computer 320
games (28, 30, 31). These video gaming platforms are used 321
with good success by several robotics simulation engines, e.g., 322
(22, 32, 33) to create complex virtual worlds with visually 323
appealing graphics. However, the gaming platforms are not 324
designed to accurately simulate the physics governing the be- 325
havior of robots and their interactions with the environment. 326
Consequently, their predictive attributes are limited owing to 327
an emphasis on plausibility rather than accuracy. 328

329 **Issue 3. Model composability needs further improve- 329**
330 **ments.** A rich universe opens up when multiple agents par- 330
331 ticipate in the same scenario, see, for instance (34). Com- 331
332 posability refers to the ability to combine, LEGO style, basic 332
333 constructs/sub-models into complex simulation scenarios. In 333
334 this approach, complex scenarios are investigated via composed 334
335 models that draw on validated, discipline-oriented, sub-models. 335
336 This calls for more than just the ability to build on a hierar- 336
337 chical representation of a model. Indeed, there is an interplay 337
338 at run-time between these sub-components that takes place in 338
339 the presence of dynamic (evolving) environments and human 339
340 participation. For instance, the sub-models communicate with 340
341 each other (agent-to-agent, agent-to-infrastructure, etc.) and 341
342 interact with each other through contact, friction, visual or 342
343 auditory cues, etc. These aspects need to be supported in a 343
344 physics-based fashion by the simulation engine, and this is 344
345 what makes this composability problem more than a “model 345
346 representation”; i.e., a pre-processing, problem. One additional 346
347 layer of complexity comes into play if a real time constraint 347
348 must be met for scenarios that include numerous robots. Com- 348
349 posability with scalability typically calls for simulators that 349
350 rely on parallel computing, which further complicates the prob- 350
351 lem at hand due to time and space coherence requirements 351
352 – robots should propagate their dynamics in the same world 352
353 time and be able to sense each other although they might run 353
354 on different hardware assets linked through a fast interconnect 354
355 fabric. There are several sources of inspiration for handling 355
356 composability, e.g., V-REP (23), which embraces composabil- 356
357 ity yet has other limitations in terms of breadth of physics 357
358 simulated. Similarly, there are computer aided design (CAD)- 358

359 to-dynamics modeling pipelines (which leverage, for instance, 420
360 SolidWorks or MATLAB), and video gaming-based solutions 421
361 that can lighten the burden of reaching composability with 422
362 scalability. Indeed, the game community has established so- 423
363 phisticated game authoring tools that implicitly handle model 424
364 composability. On the down side, they are massive chunks 425
365 of code, cumbersome to work with and, as pointed out in 426
366 Issue 2, only partially cover the robotics community’s needs 427
367 owing to emphasizing credibility-in-appearance rather than
368 accuracy-in-results.

369 **Issue 4. Simulation is not fast enough.** Robotics simu- 428
370 lation is customarily used for mechanical design or control 429
371 purposes. In controls, the simulations should run fast, in fact, 430
372 faster than real-time for model predictive control or on-line 431
373 policy inference (while not ideal, slower than real time perfor- 432
374 mance is acceptable for off-line policy inference often times 433
375 employed in Machine Learning). Presently, by and large, robot 434
376 models that only use rigid bodies run in real-time as long as the 435
377 number of bodies is in the neighborhood of 10-15 and the num- 436
378 ber of collisions with friction and contact is low (25, 35, 36). 437
379 However, the real-time constraint is daunting for models that 438
380 contain flexible/soft/deformable components and/or numerous 439
381 contacts with friction. An additional and sizable simulation 440
382 slow down is associated with scenarios that include unstruc- 441
383 tured and changing environments, e.g., deformable terrain, 442
384 cluttered environments, fluid-solid interaction, etc. Bringing 443
385 this type of physics into the model is important when robots 444
386 venture outside controlled environments and operate in com- 445
387 plex real world scenarios. Depending on the goal pursued; 446
388 i.e., mechanical design vs. controls, managing the simulation 447
389 time calls for compromises, e.g., reduced number of iterations 448
390 in a numerical algorithm, a coarser mesh for collision detec- 449
391 tion, use of rigid instead of deformable terrain, reliance on 450
392 more rudimentary sensing, use of rigid instead of compliant 451
393 elements, 2D instead of 3D dynamics, model reduction, etc. 452
394 Note that the nature of this compromise also depends on the 453
395 computing power available, which is markedly different for off- 454
396 line and on-line simulation. Indeed, a complex model can run 455
397 real-time in a mechanical design analysis, when one relies on 456
398 power-hungry hardware such as GPUs, only to run too slowly 457
399 in an on-line setup where weight and/or power constraints 458
400 limit the compute hardware options.

401 **Issue 5. Uncertainty is marginally handled.** Friction, im- 459
402 pact, contact, actuator noise, wear and tear, uncertain external 460
403 loads, complex and unstructured environments, etc., are a few 461
404 of the many sources of uncertainty that mar the operation of 462
405 a robot. These sources of uncertainty must also be present in 463
406 simulation. The uncertainties encountered are both aleatory 464
407 (due, for instance, to the complexity of the dynamic response 465
408 in the presence of friction and contact phenomena (37)) and 466
409 epistemic (e.g., unknown simulation parameters for a selected 467
410 model for friction, e.g., Coulomb friction (38)). Accounting 468
411 for uncertainty must be done during both model generation 469
412 and simulation phases. In model set up, one has to provide 470
413 mechanisms to inject uncertainty in the model, e.g., allowing 471
414 the friction coefficient to change in a deformable and hetero- 472
415 geneous terrain; the geometry of various components to be 473
416 less than perfect; the actuation forces/torques to display de- 474
417 lays, etc. In running simulations, one has to robustly handle 475
418 lack of smoothness associated with the solution of the robot 476
419 dynamics, e.g., stick-slip conditions, impact, control policies 477

420 that are nonsmooth, event-triggered changes that occur spo- 421
422 radically to suddenly change loads or boundary conditions, 423
424 etc. A perspective that might be useful is a statistical one, in 425
426 which confidence bounds gauge the extent to which one can 427
428 rely on simulation results (39). This uncertainty quantification
429 mindset is pivotal, since robots will often times have limited
430 knowledge about the environment they operate in and stimuli
431 they are subject to.

432 **Issue 6. Model calibration can be tedious.** Populating a 433
434 model with correct parameters is time consuming and most 434
435 often an ad-hoc, one-off, process. Pragmatically speaking, the 435
436 goal is to do predictive analysis, not to find parameters for 436
437 a model. This observation explains why this topic receives 437
438 less attention than the task of generating the model, which 438
439 nonetheless is populated with these very parameters that ul- 439
440 timately dictate its quality. When experimental data for the 440
441 robot is available, classical identification methods are effective 441
442 provided the parameter space is not large (40). Unfortunately, 442
443 at design phase, robots exist only as CAD drafts yet to be in- 443
444 stantiated in reality; as such, experimental data is unavailable. 444
445 Even when the robots exist, experimental data for calibration 445
446 might be hard to procure. For instance, friction and 446
447 contact simulation for rigid-wheel/deformable-terrain interac- 447
448 tion requires more than 10 parameters, which are typically 448
449 determined through a bevameter test carried out in the field 449
450 (41). Although the rover might exist, experimental data for 450
451 Martian soil is very limited and a bevameter test is out of ques- 451
452 tion. Recent efforts aimed at simplifying calibration rely on 452
453 Machine Learning and other statistical approaches to employ 453
454 iterative processes that automate what remains a labor and 454
455 time intensive process (6, 42, 43). For large parameter sets, 455
456 brute force approaches can leverage powerful processors to 456
457 perform statistically guided extensive searches for parameter 457
458 values, see, for instance, (44). 458

459 **Issue 7. Data-driven approaches (surrogate models; 459
460 replacing simulation with an oracle) are only slowly 460
461 emerging.** The standardization of robotic platforms open 461
462 the possibility to collect large amounts of data (sometimes pro- 462
463 vided by the manufacturer) in real world scenarios that could 463
464 be leveraged by Machine Learning techniques to build predic- 464
465 tive models directly from data (8). The hope is that using 465
466 statistical learning techniques, one could bypass simulation- 466
467 specific hurdles such as model generation and calibration by 467
468 constructing “oracles” that are able to predict the next system 468
469 state given its current one. The outcome of a data-driven ap- 469
470 proach might not be a complete elimination of the simulation. 470
471 The approach could be used to methodically reduce model 471
472 (and therefore computational) complexity through systematic 472
473 dimensional reduction and/or model compression (45, 46). 473
474 However, the data-driven approaches in robotics simulation 474
475 are in their infancy and principled methodologies to design 475
476 and validate data-driven models remain to be identified. In 476
477 addressing the issue at hand, one is faced with the practi- 477
478 cal challenge of developing realistic use cases and generating 478
479 enough data to represent “truth” or “reality.” This is not a 479
480 trivial task. For instance, what types of data, problems, and 480
481 level of authenticity are required to better capture and model 481
482 the socio-physical characteristics of human-robot interaction 482
483 scenarios? Note that in producing these surrogate models, one 483
484 can substitute experimental data with simulator-generated 484
485 data. Indeed, if a simulator and a model exist, the data pro-

duced by the simulator-model combo, just like experimental data, can be used to produce an “oracle” that within a controlled set of regimes can yield results close to those produced in simulation. In other words, the simulator provides the data that leads to its obsolescence.

Issue 8. Difficulties in gauging the needed level of model complexity. Complex models set up to produce highly accurate results most often lead to long run times and require a wealth of model parameters. It is not uncommon that lack of good parameters in these models leads to worse results that take longer to produce than what can be obtained using simpler models. Likewise, debugging complex models is time consuming since it is difficult to discern whether sub-par results are due to poor model parameters or to weaknesses in the modeling and numerical solution techniques anchoring the simulator. Against this backdrop, there is lack of consensus regarding when complex models are needed; i.e., at what point a model confines our ability to discover through simulation. For instance, in Machine Learning, sophisticated models are expected to better negotiate the simulation-to-reality gap; i.e., to yield simulation-learned control policies that work well on the real robot (4). Recent results show though that this gap can be successfully negotiated learning with simple models. In a “domain randomization” approach, simple and therefore expeditious models are repeatedly used to canvas broad model parameter spaces via expeditious simulation to improve control policy robustness (5). Unfortunately, this example cannot be generalized and one should be cognizant of the fact that validated simulation tools serve multiple end goals – human-in-the-loop simulation, the designing of better control policies, improving mechanical performance, auditing for safety purposes, etc. This suggests that diversity in the level of model complexity is inevitable and the practitioner has to rely on past experience, understanding of the real world problem, and knowledge of the simulation tool to make the right call insofar as the needed level of complexity in the model is concerned. Choosing a simple model for a complex problem might produce misleading results; conversely, choosing too complex of a model for a simple problem might take an unreasonable amount of effort to set up and lead to prohibitively long simulations times. These are two outcomes that each can discredit the idea of using simulation in robotics; they can also be used to make a case that simulation in robotics is part science and part practice.

Issue 9. Handling the human-robot interaction. One conspicuous challenge in HRI simulation is tied to the speed of execution: the robot simulation should be fast enough to support real-time interaction between the human and the robot model (human-in-the-loop simulation). This poses several challenges, see Issue 4. Speed of execution ceases to be a matter of concern if there is no actual human in the loop; i.e., the human component is simulated as well. Indeed, in robot training, the human is replaced with an avatar endowed with the same traits that the human would display in his/her interaction with the robot. Creating avatars is as difficult as humans are diverse, each person a unique and complex web of intertwined physical, social, emotional, cognitive, and psychological threads. Numerous empirical models have been created to abstract human behavior in robotics and virtual reality (47). Ideally, the wisdom and insights that these studies have yielded would be aggregated in priors for mathematical

models. This would mark a departure from today’s empiricism in human modeling in robotics and represent a step towards the adoption of statistical models of the human in HRI tasks. While progress has been reported in capturing mechanistic traits in HRI, e.g., models for the mechanics of the human body insofar as simulating surgery procedures is concerned (48, 49), numerous questions remain unanswered in relation to abstracting in mathematical models the psychological underpinnings that trigger in humans states of anxiety, fear, comfort, stress, etc. In this context, the ability to control and display emotions in avatars represents a prerequisite for endowing smart robots with a sense of empathy in their interaction with humans (50).

Suggested steps for making simulation more useful in robotics

The next two subsections summarize, respectively, recommendations and high-vantage-point observations that emerged at the conclusion of the simulation-in-robotics workshop.

A. “Nuts-and-bolts” recommendations. The recommendations below are made for a generic agency that considers making investments in the simulation-in-robotics area while the agency is at the stage of assembling a call for proposals. The recommendations could also be informative to someone who contemplates becoming involved in the research and development effort associated with the simulation-in-robotics topic. The list is not comprehensive; it only compiles several initiatives deemed as of higher priority.

1. Foster the development and validation of open source simulation platforms
2. Foster efforts that seek to establish open and community curated libraries of validated models
3. Organize several simulation-in-robotics grand challenge competitions
4. Encourage efforts that seek to characterize the human-robot interaction
5. Encourage simulation solutions for soft robotics
6. Emphasize use of emerging hardware architectures

Rec. 1. Foster the development and validation of open source simulation platforms. A robust and feature-rich set of four or five simulation tools available in the open-source domain is critical to advancing the state of the art in robotics. Validated open source platforms democratize the simulation-in-robotics effort and inspire/inform future, more refined open-source or commercial efforts. Trusted open source solutions are quickly embraced; support the idea of reproducibility/verifiability in science; and have the side effect of immediately raising the bar for the commercial tools, which must necessarily up the ante. Owing to the breadth of robotics applications, it is likely that no single platform will emerge as the solution of choice for all targeted simulation scenarios, which provides the rationale for the “four or five simulation platforms” recommendation above.

Rec. 2. Foster efforts that seek to establish open and community curated libraries of validated models. Customarily, simulation in robotics calls for the interplay of three types of sub-models: robots, synthetic worlds, and sensors. In some cases, the human component comes into play, and, for

599 multi-robot scenarios, one might need to simulate the commu- 600
601 nication layer. Any one of these sub-models is complex, both
602 to generate and endow with meaningful parameters, see Issue
603 6. With an eye towards scenario composability, it would be
604 useful and impactful to establish a set of freely available, ready-
605 to-go *scenario* models that build off existing robot/virtual
606 world/sensor/humans/communication sub-models. Establish-
607 ing model libraries is an arduous and long process that has
608 one prerequisite: the community must coalesce around a mod-
609 eling approach and ontology. The Unified Robot Description
610 Format (URDF) (51) represents an early step in this direction,
611 yet its modeling schema remains to be endowed with addi-
612 tional modeling elements. **The existence of a rich and broadly
613 adopted modeling language and model library will have the
614 side benefit of providing an incentive for the manufacturers
615 to augment these libraries with validated models associated
616 with their robotics solutions. Finally, it is also imperative to
617 identify new ways in which models can be validated. Fresh
618 perspectives are needed in this regard, particularly when the
619 robots simulated have not yet been realized (52).**

619 **Rec. 3. Organize several simulation-in-robotics grand
620 challenge competitions.** Over the next decade, the commu-
621 nity would benefit from a sequence of four or five grand
622 challenge competitions. Run as a sequence, perhaps two years
623 apart and akin to the 2013 DARPA’s Virtual Robotics Chal-
624 lenge (53), these competitions could pay dividends in several
625 ways. First, carefully chosen challenge themes would focus
626 the community effort. Without direction and clear purpose,
627 the community can choose to focus limited resources along
628 technical thrusts of secondary relevance. Second, a set of well-
629 chosen challenge themes would be a catalyst for cross-discipline
630 collaboration. The current robotics simulation gaps are best
631 addressed by multi-disciplinary teams, combining model de-
632 velopers and model users, particularly when the latter have
633 expertise in physical testing. **Third, such an effort will kindle
634 and foster an ecosystem build-up effort to produce the meth-
635 ods, tools, models, and validation metrics of the trade. Fourth,
636 this effort will likely produce a catalog of reliable simulation
637 platforms available, as well as a community sanctioned set of
638 recommendations that indicates which tool works well in what
639 scenarios. Lastly, it is highly likely that these competitions will
640 attract a lot public interest, which bodes well for promoting
641 the field and getting the attention of tomorrow’s roboticists.**

642 **Rec. 4. Encourage efforts that seek to characterize
643 the human-robot interaction.** The issue of establishing
644 human models that capture mechanical attributes of the body
645 and/or psychological and cognitive traits of human behav-
646 ior is cross-cutting. Applications in which HRI will come
647 into play include robotic surgery, which is relevant in surgery
648 training and remotely treating patients in remote/disaster
649 zones; assisting seniors with tasks such as dressing, personal
650 hygiene, cleaning and cooking; assisting individuals with lim-
651 ited ambulatory ability with transportation needs, etc. The
652 body of work in the area of HRI modeling is meager, which
653 explains the limited knowledge vis-à-vis the issue of human
654 cognitive performance in HRI. In this context, there is a very
655 limited set of science-based requirements and thresholds for
656 safe human-robot interaction.

657 **Rec. 5. Encourage simulation solutions for soft
658 robotics.** To date, robotics simulation has almost exclu-

sively drawn on rigid body dynamics. Indeed, the underlying 659
660 modeling is simpler, the software implementation effort is more
661 reasonable, and the simulation run-times are shorter. **Looking
662 ahead, support for soft robotics is critical in several fields, e.g.,
663 HRI and biomimetic robots.** It is anticipated that embracing
664 compliance in the robotics models will elicit new approaches to
665 handling frictional contact with the potential benefit of allevi-
666 ating numerical artifacts/paradoxes brought to the fore by the
667 rigid body model (54). Generating through simulation sensory-
668 motor data that matches the multi-resolution dynamics, noise,
669 softness, etc. of sensors and actuators **during complex tasks
670 that include both compliance and frictional contacts is poised
671 to open the door** to a systematic study of the sensory-motor
672 space for robotic manipulation and locomotion.

673 **Rec. 6. Emphasize use of emerging hardware architec-
674 tures.** Recent advances in high-bandwidth memory and large
675 core/processor counts can partially alleviate increased compu-
676 tational loads associated with terramechanics, soft robotics,
677 fluid-solid interaction and real-time simulation. Looking be-
678 yond GPU and multi-core computing, a federated approach
679 (55) in which various components of a model are handled sep-
680 arately by different solvers in a co-simulation framework would:
681 facilitate a plug-and-play vision that enables scalability of the
682 solution; open the door to contributions coming from multiple
683 groups; and enable the adoption of best-in-class solvers for
684 subproblems.

685 **B. “High-vantage-point” aspects.** Unlike the previous subsec-
686 tion, which provided pointed recommendations, the focus
687 below is on capstone observations.

- 688 1. Building a simulation-in-robotics ecosystem **requires a sus-
689 tained and** multi-disciplinary effort that poses numerous
690 open questions in basic research
- 691 2. **Simulation-in-robotics has a foundational and sizable soft-
692 ware development component to it**
- 693 3. **Simulation-in-robotics provides a grand challenge that
694 has manifest societal impact**

695 **High Level 1. Building a simulation-in-robotics ecosys-
696 tem requires a sustained and multi-disciplinary effort
697 that poses numerous open questions in basic research.**
698 Several types of simulation **techniques** have to be combined
699 to produce a simulation-in-robotics solution platform. A dy-
700 namics engine is needed to capture the time evolution of the
701 robots in environments that can be unstructured and them-
702 selves be changing in time; sensor simulation is required in
703 controlling the agents; meaningful sensor simulation is predi-
704 cated on the ability to simulate the environment and model
705 its unstructured and time-dependent nature; simulating the
706 human dimension in HRI; finally, communication simulation
707 comes into play for agent-to-agent or agent-to-infrastructure
708 communication. **Open problems that defy our current level of
709 understanding riddle each of these simulation aspects whose in-
710 terplay ultimately defines the concept of simulation in robotics.**
711 Addressing these open problems requires basic research in a
712 variety of areas: physics-based modeling (friction, contact,
713 impact, soft/compliant bodies, fluid-solid interaction, terrame-
714 chanics); numerical methods (fast real-time solvers, linear
715 solvers, optimization techniques, computational geometry, the

numerical solution of differential algebraic and partial differential equations, nonlinear finite element analysis, computational fluid dynamics, etc.); software development (hardware-aware software); and data analysis (uncertainty quantification). Serendipitously, several funded initiatives are ongoing, e.g., soft robotics (NSF) and terramechanics (DOD), and bound to have an impact for the problem at hand. Nonetheless, the majority of the simulation-in-robotics multi-disciplinary open issues, e.g., modeling the human component in HRI, sensor modeling, model composability, etc., linger and at best are tangentially addressed in a context that lacks synergy and is non-programmatic. Against this backdrop, we are of the opinion that the benefits of a broad multi-agency initiative could be twofold: stimulate fundamental research in relevant areas, and foster its rapid translation into open source simulation platforms. A broad initiative of this caliber would bring together, ideally in an international framework, research groups from academia and agile software development groups from academia, research labs, and industry.

High Level 2. Simulation-in-robotics has a foundational and sizable software development component to it. While posing significant challenges, software development is not a research activity insofar as simulation-in-robotics is concerned. Yet the process adopted for developing the necessary software infrastructure along with the terms under which the software is released play a role in **how soon simulation makes a difference in robotics**. An important aspect is whether or not the software that underlies a simulation-in-robotics initiative should be released as open source. Likewise, there are several licenses, some more permissive than others, vis-à-vis how open-source can be used/modified/distributed. The salient point is that software that solves the problem at hand is desirable in any form. Perhaps, at the onset of a simulation-in-robotics initiative open source released under a permissive license such as MIT is more attractive only for the reason that a component of it, be it a graphical user interface, data input/output facilities, a particular algorithm, a collision detection implementation, etc., might be recycled by another effort that itself might be open or closed source. In our experience, the argument that an open source code grows faster owing to contributions from volunteers has proven largely unsubstantial. Indeed, the level of skill and expertise required to make meaningful contributions to a project are prohibitive, particularly early on in the trail-blazing phase of the project. In fact, the point in time in the software life cycle when volunteers can help marks the moment when the project would ideally go commercial or be sponsored by such an entity. This brings up the question of who should develop the software that enables the simulation-in-robotics vision. Encouraging domain experts to engage in software development pursuits that have a manifest translation attribute; i.e., demonstrating new algorithms, modeling approaches, etc., would be beneficial, particularly at the onset of the initiative and when done with a mindset of generating open-source software. Ideally, these domain-expert generated software components would be recycled by more mature simulation platforms. In this ecosystem, as the field matures, one can hope that bigger and perhaps commercial entities would step in to carry the burden of adding the features of convenience that accelerate solution adoption.

High Level 3. Simulation-in-robotics provides a grand challenge that has manifest societal impact. It is this

group's belief that computer simulation can and should play an important role in smart robotics. We take our cue from the enthusiastic adoption and broad impact that computer simulation has had in other industries and endeavors – from building cars and airplanes to planetary exploration. Yet compared to CAD, computer aided manufacturing (CAM) and CAE solutions that anchor both the product life-cycle in industry and a vigorous research enterprise in academia, the simulation in robotics field is in its infancy. Moreover, beyond lack of maturity, simulation in robotics is faced with the task of serving user groups pulling in different directions by virtue of them being engaged in different activities such as *design* (will it break? is it fast enough? can we build it?), *controls* (how can we make it reconfigure? how does it climb stairs? how does it work with other robots? will it work under limited sensing?), *machine learning* (learn gradually without forgetting; how do I close the sim-to-real gap?) and *artificial intelligence* (when and how to express empathy?). Lastly, by comparison with CAD/CAM/CAE, simulation in robotics poses unique and truly multi-disciplinary challenges, some of them summarized in this document. While established commercial CAD/CAM/CAE solution providers, e.g., MSC.ADAMS, Siemens, Dassault Systèmes, FunctionBae, etc., are anticipated to gradually address the needs of the robotics community, our near-term hopes are pinned on nimbler and more focused platforms, e.g., Bullet (25), Chrono (36), DART (26), Drake (56), MuJoCo (35), ODE (24), SOFA (57). These platforms are by and large open source; are plugged deeper into the research community; and have the flexibility to rapidly translate modeling, numerical methods, sensor simulation, graphics, and emerging hardware architectures breakthroughs into advances that amplify the impact that simulation plays in robotics.

Conclusions

This contribution outlines benefits that simulation can provide in the smart robotics design process; and barriers that need to be overcome for simulation to deliver on its potential in this arena. Sharing the viewpoint that simulation is not a goal in itself but a means to an end, we believe that undertaking a focused, coordinated and sustained research and software development effort in this area is timely. In the process, the simulation community will have to address research questions at the intersection of computer science, mechanical engineering, electrical engineering, cognitive science, and applied mathematics. **Without a systematic, guided, and all-encompassing effort, advancing the state of the art will be marred by trial-and-error detours.** The pressing question is how to jump start a robotics-simulation cross-pollination process that would speedily transition the effort from the “academic debate” phase into a “simulation-enabled building and demonstration of technology” phase. This transition can be catalyzed by a sustained decade-long financial commitment, which would ensure funding for cross-disciplinary efforts that promote collaboration, competition and compilation of open repositories of **validated** models and source code. As witnessed in the aerospace and automotive industry, the paradigm shift to digital, while manifestly impactful, took decades to coalesce. **Learning from this experience, the hope is that simulation will lead to breakthroughs in the design of smart robots in a matter of years rather than decades.**

837 Acknowledgments and disclaimers

838 The workshop that led to this manuscript was organized with
839 support from National Science Foundation under grant NRI-
840 183012. We would also like to acknowledge the logistical
841 support provided by National Institute of Standards and Tech-
842 nology, which hosted the workshop event. We grateful for the
843 input provided by more than other 30 experts who attended
844 the event but are not listed as co-authors on this document.

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854 over, the opinions expressed by authors contributing to this
855 manuscript do not necessarily reflect the opinions of the agen-
856 cies or the institutions with which the authors are affiliated.

857 References

858 1. Anderson, S. and Boots, B. and Byravan, A. and Drumwright, E. and Duriez, C. and Fox, D.
859 and Hager, G. and Hodgins, J. and Jain, A. and Kapoor, A. and Koditschek, D. and Koenig,
860 N. and Lee, E. and Li, C. and Liu, K. and Meier, F. and Negrut, D. and Rajhans, A. and
861 Righetti, L. and Rodriguez, A. and Schaal, S. and Tan, J. and Tassa, Y. and , E. and Trinkle, J.
862 (2018) Final Report and Working Documents: NSF/NIST/DOD Workshop on Using Modeling
863 and Simulation in Robotics (<https://sbel.wisc.edu/simulation-in-robotics-2018/>). Accessed:
864 2019-01-04.

865 2. Byravan, A. and Fox, D. and Meier, F. and Negrut, D. (2018) NSF/NIST/DOD Workshop on
866 Using Modeling and Simulation in Robotics (<https://www.nist.gov/news-events/events/2018/04/simulation-and-machine-learning-robotics>). Accessed: 2018-12-09.

867 3. Kober J, Bagnell A, Peters J (2013) Reinforcement learning in robotics: A survey. *The Inter-*
868 *national Journal of Robotics Research* 32(11):1238–1274.

869 4. Jakobi N, Husband P, Harvey I (1995) Noise and the reality gap: The use of simulation in
870 evolutionary robotics in *European Conference on Artificial Life*. (Springer), pp. 704–720.

871 5. Tobin J, et al. (2017) Domain randomization for transferring deep neural networks from sim-
872 ulation to the real world in *2017 IEEE/RSJ international conference on intelligent robots and*
873 *systems (IROS)*. (IEEE), pp. 23–30.

874 6. Chebotar Y, et al. (2019) Closing the sim-to-real loop: Adapting simulation randomization with
875 real world experience in *2019 International Conference on Robotics and Automation (ICRA)*.
876 (IEEE), pp. 8973–8979.

877 7. Andrychowicz M, et al. (2020) Learning dexterous in-hand manipulation. *The International*
878 *Journal of Robotics Research* 39(1):3–20.

879 8. Deisenroth M, Neumann G, Peters J (2013) *A Survey on Policy Search for Robotics*, Founda-
880 tions and Trends® in Robotics Series. (Now Publishers).

881 9. Serban R, Taylor M, Negrut D, Tasora A (2019) Chrono: Vehicle Template-Based Ground
882 Vehicle Modeling and Simulation. *Intl. J. Veh. Performance* 5(1):18–39.

883 10. Fisher M, Dennis L, Webster M (2013) Verifying autonomous systems. *Communications of the*
884 *ACM* 56(9):84–93.

885 11. Luckcuck M, Farrell M, Dennis LA, Dixon C, Fisher M (2019) Formal specification and verifica-
886 tion of autonomous robotic systems: A survey. *ACM Computing Surveys (CSUR)* 52(5):1–41.

887 12. Burgard W, Moors M, Stachniss C, Schneider FE (2005) Coordinated multi-robot exploration.
888 *IEEE Transactions on robotics* 21(3):376–386.

889 13. Tan Y, Zheng Zy (2013) Research advance in swarm robotics. *Defence Technology* 9(1):18–
890 39.

891 14. Akhtar N, Mian A (2018) Threat of adversarial attacks on deep learning in computer vision: A
892 survey. *IEEE Access* 6:14410–14430.

893 15. Winfield AF, Jirotkra M (2018) Ethical governance is essential to building trust in robotics and
894 artificial intelligence systems. *Philosophical Transactions of the Royal Society A: Mathemati-*
895 *cal, Physical and Engineering Sciences* 376(2133):20180085.

896 16. Markidis S, Der Chien SW, Laure E, Peng IB, Vetter JS (2018) Nvidia tensor core program-
897 mability, performance & precision in *2018 IEEE International Parallel and Distributed Processing*
898 *Symposium Workshops (IPDPSW)*. (IEEE), pp. 522–531.

899 17. Ingrand F, Ghallab M (2017) Deliberation for autonomous robots: A survey. *Artificial Intelli-*
900 *gence* 247:10–44.

901 18. Fong T, Nourbakhsh I, Dautenhahn K (2003) A survey of socially interactive robots. *Robotics*
902 *and autonomous systems* 42(3-4):143–166.

903 19. Metcalfe J, et al. (2017) Building a framework to manage trust in automation in *Micro-and*
904 *Nanotechnology Sensors, Systems, and Applications IX*. (International Society for Optics
905 and Photonics), Vol. 10194, p. 101941U.

906 20. Koenig NP, Howard A (2004) Design and use paradigms for Gazebo, an open-source multi-
907 robot simulator. in *IROS*. (Citeseer), Vol. 4, pp. 2149–2154.

908 21. Aguero C, et al. (2015) Inside the virtual robotics challenge: Simulating real-time robotic

disaster response. *Automation Science and Engineering, IEEE Transactions on* 12(2):494–
506. 910

22. Carpin S, Lewis M, Wang J, Balakirsky S, Scrapper C (2007) USARSim: a robot simulator
911 for research and education in *Proceedings 2007 IEEE International Conference on Robotics*
912 *and Automation*. (IEEE), pp. 1400–1405. 913

23. Rohmer E, Singh SP, Freese M (2013) V-REP: A versatile and scalable robot simulation
914 framework in *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems*.
915 (IEEE), pp. 1321–1326. 916

24. Smith RL (2015) Open Dynamics Engine. Available online at <http://www.ode.org/>. 917

25. Coumans E, Bai Y (2016–2019) Pybullet, a python module for physics simulation for games,
918 robotics and machine learning (<http://pybullet.org>). 919

26. Lee J, et al. (2018) DART: Dynamic animation and robotics toolkit. *The Journal of Open*
920 *Source Software* 3(22):500. 921

27. Sherman MA, Seth A, Delp SL (2011) Simbody: multibody dynamics for biomedical research.
922 *Procedia IUTAM* 2:241–261. 923

28. NVIDIA (2019) PhysX simulation engine. Available online at <http://developer.nvidia.com/object/physx.html>. 924

29. Tasora A, et al. (2016) Chrono: An open source multi-physics dynamics engine in *High Per-*
925 *formance Computing in Science and Engineering – Lecture Notes in Computer Science*, ed.
926 Kozubek T. (Springer), pp. 19–49. 927

30. Epic Games (2020) Unreal Engine (<https://www.unrealengine.com>). 928

31. Unity3D (2016) Main Website (<https://unity3d.com/>). Accessed: 2016-06-09. 929

32. Dosovitskiy A, Ros G, Codevilla F, Lopez A, Koltun V (2017) CARLA: An open urban driving
930 simulator in *Proceedings of the 1st Annual Conference on Robot Learning*. pp. 1–16. 931

33. Shah S, Dey D, Lovett C, Kapoor A (2018) Airsim: High-fidelity visual and physical simulation
932 for autonomous vehicles in *Field and service robotics*. (Springer), pp. 621–635. 933

34. Simmons R, et al. (2000) Coordination for multi-robot exploration and mapping in *Aaai/laai*.
934 pp. 852–858. 935

35. Todorov E, Erez T, Tassa Y (2012) Mujoco: A physics engine for model-based control in *2012*
936 *IEEE/RSJ International Conference on Intelligent Robots and Systems*. (IEEE), pp. 5026–
937 5033. 938

36. Project Chrono (2020) Chrono: An Open Source Framework for the Physics-Based Simula-
939 tion of Dynamic Systems (<http://projectchrono.org>). Accessed: 2020-03-03. 940

37. Yu KT, Bauza M, Fazeli N, Rodriguez A (2016) More than a million ways to be pushed. A high-
941 fidelity experimental dataset of planar pushing in *2016 IEEE/RSJ international conference on*
942 *intelligent robots and systems (IROS)*. (IEEE), pp. 30–37. 943

38. Fazeli N, Zapolsky S, Drumwright E, Rodriguez A (2020) Fundamental limitations in perfor-
944 mance and interpretability of common planar rigid-body contact models in *Robotics Research*.
945 (Springer), pp. 555–571. 946

39. Chenney S, Forsyth D (2000) Sampling plausible solutions to multi-body constraint problems
947 in *Proceedings of the 27th annual conference on Computer graphics and interactive tech-*
948 *niques*. pp. 219–228. 949

40. Ljung L (1999) *System identification: Theory for the user*. (Prentice Hall, Saddle River, New
950 Jersey), 2nd edition. 951

41. Wong JY (1989) *Terramechanics and off-road vehicles*. (Elsevier). 952

42. Abbeel P, Quigley M, Ng AY (2006) Using inaccurate models in reinforcement learning in
953 *Proceedings of the 23rd international conference on Machine learning*. pp. 1–8. 954

43. Rajeswaran A, Ghotra S, Ravindran B, Levine S (2016) Epopot: Learning robust neural net-
955 work policies using model ensembles. 956

44. Collins J, Brown R, Leitner J, Howard D (2020) Traversing the reality gap via simulator tuning.
957 *arXiv preprint arXiv:2003.01369*. 958

45. Farhat C, Avery P, Chapman T, Cortial J (2014) Dimensional reduction of nonlinear finite
959 element dynamic models with finite rotations and energy-based mesh sampling and weight-
960 ing for computational efficiency. *International Journal for Numerical Methods in Engineering*
961 98(9):625–662. 962

46. Goury O, Duriez C (2018) Fast, generic, and reliable control and simulation of soft robots
963 using model order reduction. *IEEE Transactions on Robotics* 34(6):1565–1576. 964

47. Pantic M, Pentland A, Nijholt A, Huang TS (2007) Human computing and machine un-
965 derstanding of human behavior: A survey in *Artificial Intelligence for Human Computing*.
966 (Springer), pp. 47–71. 967

48. Courtecuisse H, et al. (2014) Real-time simulation of contact and cutting of heterogeneous
968 soft-tissues. *Medical image analysis* 18(2):394–410. 969

49. Albani JM, Lee DI (2007) Virtual reality-assisted robotic surgery simulation. *Journal of En-*
970 *dourology* 21(3):285–287. 971

50. Nomura T, Kanda T, Suzuki T, Kato K (2008) Prediction of human behavior in human-robot
972 interaction using psychological scales for anxiety and negative attitudes toward robots. *IEEE*
973 *transactions on robotics* 24(2):442–451. 974

51. Robot Operating System (2018) The Unified Robot Description Format (URDF) (<http://wiki.ros.org/urdf>). Accessed: 2018-02-15. 975

52. Pepper C, Balakirsky S, Scrapper C (2007) Robot simulation physics validation in *Proceed-*
976 *ings of the 2007 Workshop on Performance Metrics for Intelligent Systems*. pp. 97–104. 977

53. Agüero CE, et al. (2015) Inside the virtual robotics challenge: Simulating real-time robotic
978 disaster response. *IEEE Transactions on Automation Science and Engineering* 12(2):494–
979 506. 980

54. Stewart DE (2000) Rigid-body dynamics with friction and impact. *SIAM Review* 42(1):3–39. 981

55. Enge-Rosenblatt O, Clauß C, Schneider A, Schneider P (2011) Functional digital mock-up
982 and the functional mock-up interface-two complementary approaches for a comprehensive
983 investigation of heterogeneous systems in *Proceedings of the 8th International Modelica Con-*
984 *ference; March 20th-22nd; Technical University; Dresden; Germany*. (Linköping University
985 Electronic Press), No. 063, pp. 748–755. 986

56. Tedrake R (2019) Drake: A planning, control, and analysis toolbox for nonlinear dynamical
987 systems (<http://drake.mit.edu>). Accessed April 2019. 988

57. Faure F, et al. (2012) Sofa: A multi-model framework for interactive physical simulation in *Soft*
989 *tissue biomechanical modeling for computer assisted surgery*. (Springer), pp. 283–321. 990