Institute of Mechatronic Systems
imes Leibniz Universität Hannover

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Investigation of Transfer Learning in Contact-Body Classification for Human-Robot Collaboration with Parallel Robots

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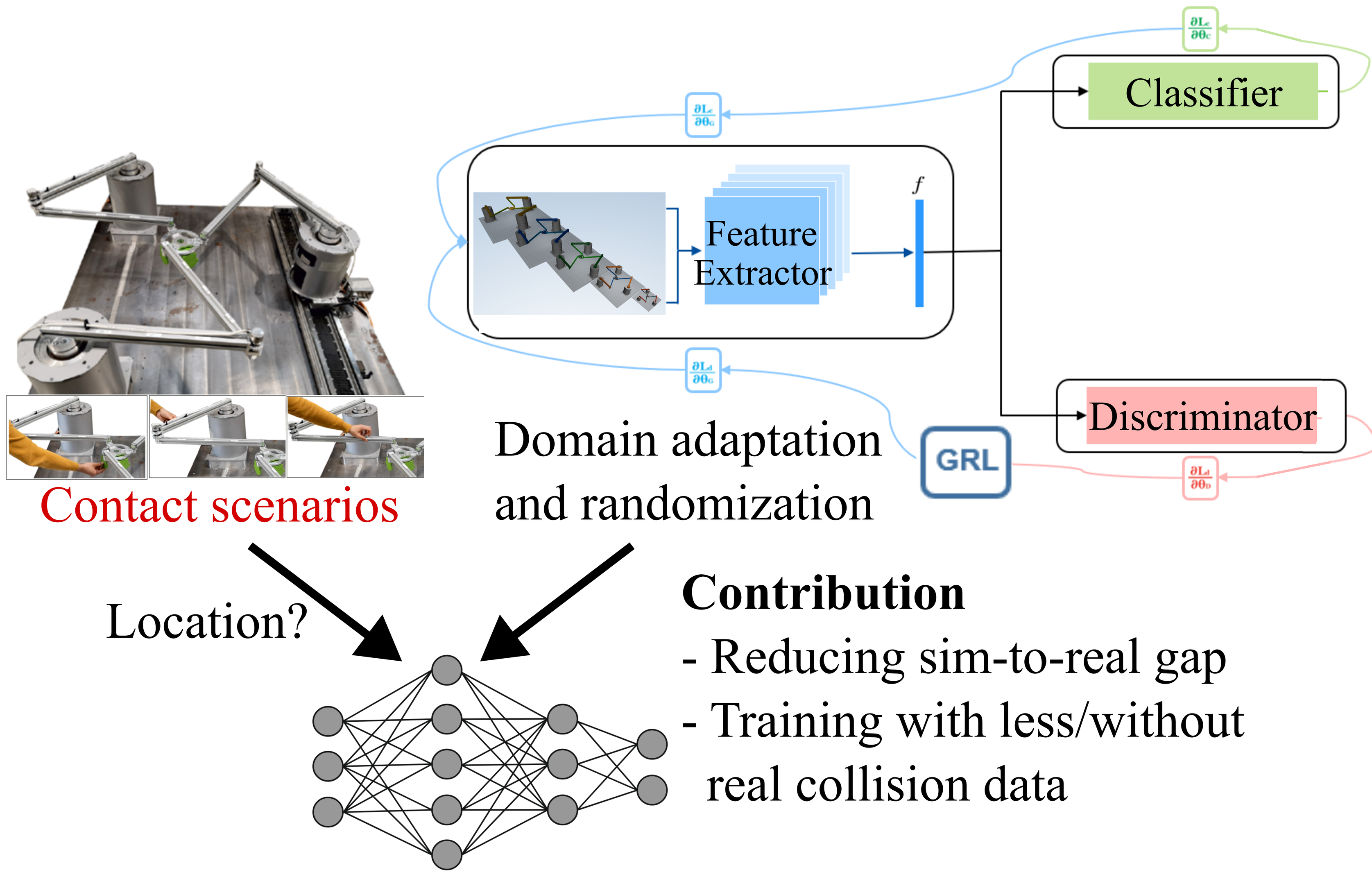
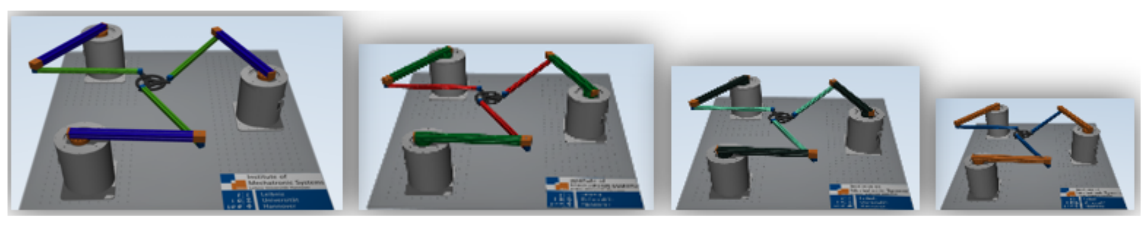
Research Question & Contributions

- Supervised-learning methods hold significant potential for contact classification in human-robot collaboration (HRC). Training data-driven models typically requires large datasets. Data collection in the case of HRC is costly, risky and complex. → **How to train a data-driven model with less/without real collision data? How can the existing sim-to-real gap be reduced?**
- Differently scaled parallel robots (PRs) are simulated as source domains, which are generated via domain randomization by varying physical parameters of the PRs
- To overcome the sim-to-real gap, domain adaptation using domain adversarial neural networks (DANNs) is applied, which enables models to learn domain-independent representations



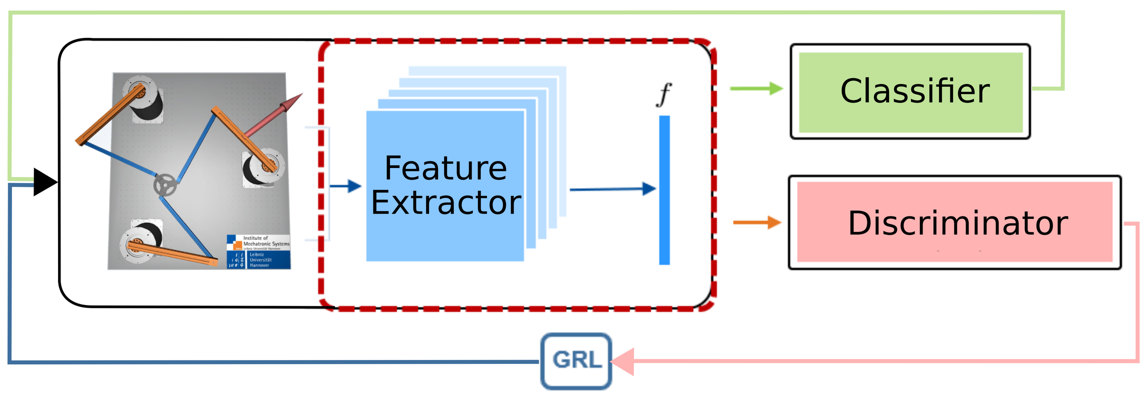
Domain Randomization & Adaptation

Domain Randomization



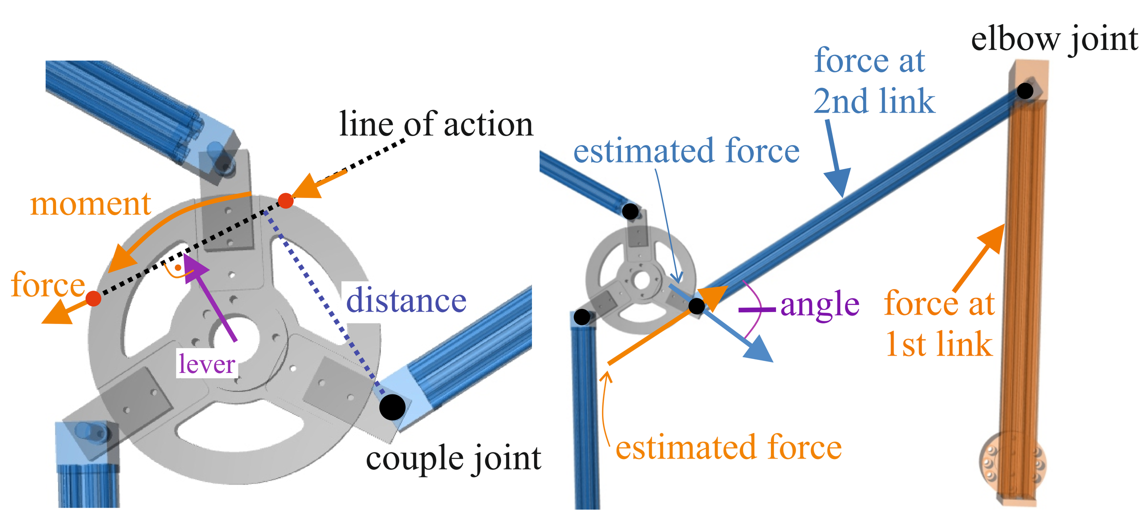
- Kinematics and inertial parameters of PRs scaled within MuJoCo simulation
- Various contact scenarios simulated for scaled PRs with different joint-angle configurations, contact positions and contact forces
- Simulated contact scenarios are utilized in adversarial collided-body classification

Adversarial Collided-Body Classification



- DANN is trained to perform effectively contact-body classification on data from both source and target domains
- Feature extractor is designed to learn domain-independent features through gradient-reversal layer and discriminator

Physically Modeled Features



- Estimated external force and direction of its line of action are features
- Minimal distance and angle allow to distinguish between contact bodies

Results

Sim-To-Sim

Source	Target	Accuracy [%]
Factor 1.5	1	82.9
Factor 2	1	77.8
Factor 2.5	1	71.4
Factor 3	1	64.7
Multi-DA 1.5–3	1	86.2

- Simulation environment of PR without scaling is used as target domain
- Accuracy decreases using larger PRs as source domain
- Highest accuracy using multiple various scaled PRs as source domain (Multi-DA)

Sim-To-Real

Transfer task	Method	Accuracy [%]
Real-to-real	FNN	79.82
Sim-to-real	FNN	61.6
Sim-to-real	DANN	70.2
Sim-to-real	Multi-DANN	72.8

- Real-world PR selected as target and scaled simulated PRs as source domains
- Training exclusively with simulated data and without adversarial training highlights sim-to-real gap, which can be reduced to 7% using Multi-DANN

Sim/Real-To-Real

Transfer task	Method	Accuracy [%]
Real-to-real	FNN	79.82
Sim/real-to-real	DANN	86.9
Sim/real-to-real	Multi-DANN	87.4

- Training data contains randomized simulation models and data from test bench
- Combination of simulation and real data increases accuracy by 8%
- Using simulation improves classification and reduces dangerous, expensive, and time-consuming data collection