Novelty Assessment Report

Paper: DemoGrasp: Universal Dexterous Grasping from a Single Demonstration
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Abstract

Universal grasping with multi-fingered dexterous hands is a fundamental challenge in robotic manipulation. While recent approaches successfully learn closed-loop grasping policies using reinforcement learning (RL), the inherent difficulty of high-dimensional, long-horizon exploration necessitates complex reward and curriculum design, often resulting in suboptimal solutions across diverse objects. We propose DemoGrasp, a simple yet effective method for learning universal dexterous grasping. We start from a single successful demonstration trajectory of grasping a specific object and adapt to novel objects and poses by editing the robot actions in this trajectory: changing the wrist pose determines where to grasp, and changing the hand joint angles determines how to grasp. We formulate this trajectory editing as a single-step Markov Decision Process (MDP) and use RL to optimize a universal policy across hundreds of objects in parallel in simulation, with a simple reward consisting of a binary success term and a robot–table collision penalty. In simulation, DemoGrasp achieves a 95% success rate on DexGraspNet objects using the Shadow Hand, outperforming previous state-of-the-art methods. It also shows strong transferability, achieving an average success rate of 84.6% across diverse dexterous hand embodiments on six unseen object datasets, while being trained on only 175 objects. Through vision-based imitation learning, our policy successfully grasps 110 unseen real-world objects, including small, thin items. It generalizes to spatial, background, and lighting changes, supports both RGB and depth inputs, and extends to language-guided grasping in cluttered scenes.

Core Task Landscape

This paper addresses: **Universal Dexterous Grasping with Multi-Fingered Robotic Hands**
A total of **50 papers** were analyzed and organized into a taxonomy with **21 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:
- **Learning-Based Grasp Synthesis and Control**
- **Model-Based Grasp Planning and Control**
- **Specialized Grasping Tasks and Scenarios**
- **Hand Design and Embodiment**
- **Sensing and Perception for Grasping**
- **Theoretical Foundations and Human Grasping Analysis**
- **Precision and Power Grasp Transitions**
- **Reviews and Surveys**

Complete Taxonomy Tree

- Universal Dexterous Grasping with Multi-Fingered Robotic Hands Survey Taxonomy
- Learning-Based Grasp Synthesis and Control
  - Reinforcement Learning for Grasping and Manipulation
  - Deep RL for Dexterous Manipulation Tasks (3 papers)
    - [8] Dexterous manipulation for multi-fingered robotic hands with reinforcement learning: A review (Chunmiao Yu, 2022) View paper
    - [24] Interactive learning for multi-finger dexterous hand: A model-free hierarchical deep reinforcement learning approach (Baojiang Li, 2024) View paper
    - [31] Grasp with push policy for multi-finger dexterity hand based on deep reinforcement learning (Baojiang Li, 2024) View paper
  - RL with Bionic Reflexes and Sensorimotor Integration (2 papers)
    - [21] Soft-Grasping With an Anthropomorphic Robotic Hand Using Spiking Neurons (Tieck, 2020) View paper
    - [22] Reinforcement Learning-Based Bionic Reflex Control for Anthropomorphic Robotic Grasping exploiting Domain Randomization (Hirakjyoti Basumatary, 2023) View paper
  - Human-Inspired Learning Approaches
  - Imitation Learning from Human Demonstrations (4 papers)
    - [2] Generalization of human grasping for multi-fingered robot hands (H. B. Amor, 2012) View paper
    - [7] Learning human-like functional grasping for multifinger hands from few demonstrations (Wei Wei, 2024) View paper
    - [11] Grasp like humans: Learning generalizable multi-fingered grasping from human proprioceptive sensorimotor integration (Ce Guo, 2025) View paper
    - [16] Learning from humans how to grasp: a data-driven architecture for autonomous grasping with anthropomorphic soft hands (C. D. Santina, 2019) View paper
  - RL with Human Pose Priors and Synergies (4 papers)
    - [38] Natural object manipulation using anthropomorphic robotic hand through deep reinforcement learning and deep grasping probability network (Edwin Valarezo Añazco, 2020) View paper

- ■ [39] Reward Shaping to Learn Natural Object Manipulation With an Anthropomorphic Robotic Hand and Hand Pose Priors via On-Policy Reinforcement Learning (Patricio Rivera, 2021) View paper
- ■ [46] Human-like Object Grasping and Relocation for an Anthropomorphic Robotic Hand with Natural Hand Pose Priors in Deep Reinforcement Learning (Edwin Valarezo Añazco, 2019) View paper
- ■ [47] Object Manipulation with an Anthropomorphic Robotic Hand via Deep Reinforcement Learning with a Synergy Space of Natural Hand Poses (Patricio Rivera, 2021) View paper
  - ○ Cross-Embodiment and Generalization Methods ★ (3 papers)
  - ○ [0] DemoGrasp: Universal Dexterous Grasping from a Single Demonstration (Anon et al., 2026) View paper
  - ○ [25] CEDex: Cross-Embodiment Dexterous Grasp Generation at Scale from Human-like Contact Representations (Wu Zhiyuan, 2025) View paper
  - ○ [37] D (r, o) grasp: A unified representation of robot and object interaction for cross-embodiment dexterous grasping (Wei Zhen-yu, 2024) View paper
  - ○ Deep Learning for Grasp Detection and Planning (2 papers)
  - ○ [5] Exploring Deep Learning Grasping Models with Soft Anthropomorphic Robotic Hands (Daniele Bernardini, 2025) View paper
  - ○ [30] Attention based visual analysis for fast grasp planning with multi-fingered robotic hand (Deng Zhen, 2022) View paper
- • Model-Based Grasp Planning and Control
  - ○ Contact and Force-Based Grasp Planning (2 papers)
  - ○ [13] Power grasp planning for anthropomorphic robot hands (Máximo A. Roa, 2012) View paper
  - ○ [14] Model-based strategy for grasping 3D deformable objects using a multi-fingered robotic hand (Lazher Zaidi, 2017) View paper
  - ○ Adaptive and Reactive Grasping Control (1 papers)
  - ○ [18] Research on adaptive grasping with object pose uncertainty by multi-fingered robot hand (Shaowei Fan, 2018) View paper
- • Specialized Grasping Tasks and Scenarios
  - ○ Multi-Object and Sequential Grasping (2 papers)
  - ○ [4] Grasp multiple objects with one hand (Yuyang LI, 2024) View paper
  - ○ [41] Grasping a Handful: Sequential Multi-Object Dexterous Grasp Generation (Haofei Lu, 2025) View paper
  - ○ Articulated Object Manipulation (2 papers)
  - ○ [3] Gamma: Generalizable articulation modeling and manipulation for articulated objects (Qiaojun Yu, 2024) View paper
  - ○ [35] GMAP: Generalized Manipulation of Articulated Objects in Robotic Using Pre-trained Model (Hongliang Zeng, 2025) View paper
  - ○ Context-Aware and Functional Grasping (2 papers)
  - ○ [12] MagicHand: Context-Aware Dexterous Grasping Using an Anthropomorphic Robotic Hand (Jindong Tan, 2020) View paper
  - ○ [20] Toward human-like grasp: Functional grasp by dexterous robotic hand via object-hand semantic representation (Tianqiang Zhu, 2023) View paper
  - ○ Human-Robot Collaborative Grasping (1 papers)
  - ○ [28] Human-Robot Collaborative Tele-Grasping in Clutter With Five-Fingered Robotic Hands (Yayu Huang, 2025) View paper
- • Hand Design and Embodiment
  - ○ Soft and Compliant Hand Designs (4 papers)
  - ○ [1] A soft-robotic approach to anthropomorphic robotic hand dexterity (Jianshu Zhou, 2019) View paper
  - ○ [34] Robust Anthropomorphic Robotic Manipulation through Biomimetic Distributed Compliance (Junge, 2024) View paper
  - ○ [44] A novel type of compliant and underactuated robotic hand for dexterous grasping (Raphael Deimel, 2016) View paper
  - ○ [49] A dexterous soft robotic hand for delicate in-hand manipulation (Sylvain Abondance, 2020) View paper
  - ○ Anthropomorphic and Biomimetic Hand Architectures (4 papers)
  - ○ [9] Design of a highly biomimetic anthropomorphic robotic hand towards artificial limb regeneration (Zhe Xu, 2016) View paper
  - ○ [10] A new anthropomorphic robotic hand (I. Gaiser, 2008) View paper
  - ○ [33] Design and implementation of an anthropomorphic hand for replicating human grasping functions (C. Xiong, 2016) View paper
  - ○ [50] Integrated linkage-driven dexterous anthropomorphic robotic hand (Uikyum Kim, 2021) View paper
  - ○ Underactuated and Hybrid Hand Mechanisms (5 papers)
  - ○ [29] Design Principle of a Dual-Actuated Robotic Hand With Anthropomorphic Self-Adaptive Grasping and Dexterous Manipulation Abilities (Bai-Yang Sun, 2022) View paper
  - ○ [32] HADAR Hand: 13-DoF Hybrid Actuation-Based Dextrous Anthropomorphic Robotic Hand (Prashanth Jonna, 2025) View paper
  - ○ [36] Design and experimental evaluation of a new modular underactuated multi-fingered robot hand (Shufeng Tang, 2020) View paper
  - ○ [43] Maximizing anthropomorphic grasping abilities of bio-inspired underactuated robotic hands (Jiaji Ma, 2025) View paper
  - ○ [48] A dexterous, reconfigurable, adaptive robot hand combining anthropomorphic and interdigitated configurations (Geng Gao, 2021) View paper
  - ○ Versatile and Reconfigurable Hand Designs (1 papers)
  - ○ [42] Development of a versatile robotic hand toward jig-less assembly of a shaft-shaped part (Kohei Shibata, 2023) View paper
- • Sensing and Perception for Grasping
  - ○ Tactile and Visual-Tactile Sensing (2 papers)
  - ○ [17] Tactile sensing soft fingertip with dual air bag structure for an anthropomorphic robotic hand (Jipeng Yin, 2025) View paper
  - ○ [26] Dexterous object manipulation by a multi-fingered robotic hand with visual-tactile fingertip sensors (Seung-Hyun Choi, 2020) View paper
  - ○ Vision-Based Perception and 3D Understanding (1 papers)
  - ○ [19] A versatile robotic hand with 3D perception, force sensing for autonomous manipulation (Correll, 2024) View paper
- • Theoretical Foundations and Human Grasping Analysis (1 papers)
  - ○ [23] Human-inspired representation of object-specific grasps for anthropomorphic hands (Julia Starke, 2020) View paper
- • Precision and Power Grasp Transitions (1 papers)
  - ○ [27] From Power to Precision: Learning Fine-grained Dexterity for Multi-fingered Robotic Hands (Jianglong Ye, 2025) View paper
- • Reviews and Surveys (4 papers)
  - ○ [6] Grasp and dexterous manipulation of multi-fingered robotic hands: a review from a control view point (Ryuta Ozawa, 2017) View paper
  - ○ [15] The developments and challenges towards dexterous and embodied robotic manipulation: A survey (Li Gaofeng, 2025) View paper

- [40] Trends and challenges in robot manipulation (Aude Billard, 2019) View paper
- [45] Anthropomorphic robotic hands: a review (Erika Nathalia Gama Melo, 2014) View paper

Narrative

Core task: universal dexterous grasping with multi-fingered robotic hands. The field organizes itself around several complementary perspectives. Learning-Based Grasp Synthesis and Control encompasses data-driven approaches that leverage reinforcement learning, imitation learning, and neural network architectures to acquire grasping policies, often emphasizing cross-embodiment transfer and generalization across diverse hand morphologies. Model-Based Grasp Planning and Control focuses on analytical methods grounded in contact mechanics, optimization, and classical control theory. Specialized Grasping Tasks and Scenarios address domain-specific challenges such as deformable objects, multi-object manipulation, and functional grasping requirements. Hand Design and Embodiment explores the mechanical and actuation principles underlying anthropomorphic and underactuated hands, while Sensing and Perception for Grasping investigates tactile, visual, and multimodal feedback integration. Theoretical Foundations and Human Grasping Analysis draw insights from biomechanics and neuroscience, and a smaller cluster examines Precision and Power Grasp Transitions. Reviews and Surveys provide periodic snapshots of progress across these branches.

Within the learning-based domain, a particularly active line of work targets cross-embodiment generalization—enabling policies trained on one hand design to transfer to others with minimal retraining. DemoGrasp[0] situates itself squarely in this cluster, proposing demonstration-driven methods that bridge morphological differences. Nearby efforts such as CEDex[25] and D r o Grasp[37] similarly emphasize transferability and data efficiency, though they may differ in whether they rely on large-scale simulation, real-world human demonstrations, or hybrid strategies. A recurring tension across these works involves balancing the richness of hand-specific priors against the flexibility needed for universal applicability. Meanwhile, other branches like Gamma[3] and Grasp Multiple Objects[4] explore task-level generalization rather than embodiment transfer, highlighting the field's dual focus on hardware diversity and task complexity. DemoGrasp[0] thus represents an effort to leverage human expertise for cross-platform dexterity, contrasting with purely simulation-driven or model-based alternatives.

Related Works in Same Category

The following **2 sibling papers** share the same taxonomy leaf node with the original paper:

1. CEDex: Cross-Embodiment Dexterous Grasp Generation at Scale from Human-like Contact Representations

Authors: Wu Zhiyuan, Potamias, Rolandos Alexandros, Zhiyuan Wu, Zhang Xuyang, et al. (15 authors total) | **Year/Venue**: 2025 • arXiv.org | **URL**: View paper

Abstract

Cross-embodiment dexterous grasp synthesis refers to adaptively generating and optimizing grasps for various robotic hands with different morphologies. This capability is crucial for achieving versatile robotic manipulation in diverse environments and requires substantial amounts of reliable and diverse grasp data for effective model training and robust generalization. However, existing approaches either rely on physics-based optimization that lacks human-like kinematic understanding or require ...

Relationship Analysis

Both papers belong to the Cross-Embodiment and Generalization Methods category, focusing on enabling grasp transfer across diverse hand morphologies. While DemoGrasp learns universal grasping policies through demonstration editing and reinforcement learning that generalizes across embodiments, CEDex generates cross-embodiment grasps by bridging human grasping kinematics with robot kinematics through contact representations and optimization. The key difference is that DemoGrasp uses RL-based policy learning from a single demonstration for closed-loop control, whereas CEDex employs a data generation pipeline using human contact priors and kinematic alignment to create large-scale grasp datasets.

2. D (r, o) grasp: A unified representation of robot and object interaction for cross-embodiment dexterous grasping

Authors: Wei Zhen-yu, XU Zhixuan, Zhenyu Wei, Guo Jing-xiang, Zhixuan Xu, et al. (16 authors total) | **Year/Venue**: 2024 | **URL**: View paper

Abstract

Dexterous grasping is a fundamental yet challenging skill in robotic manipulation, requiring precise interaction between robotic hands and objects. In this paper, we present $\mathcal{D(R,O)}$ Grasp, a novel framework that models the interaction between the robotic hand in its grasping pose and the object, enabling broad generalization across various robot hands and object geometries. Our model takes the robot hand's description and object point cloud as inputs and efficiently predicts kinematic...

Relationship Analysis

Both papers belong to the Cross-Embodiment and Generalization Methods category, focusing on enabling dexterous grasping across diverse hand morphologies. They overlap in addressing universal grasping across multiple robotic hands and object categories, with both demonstrating cross-embodiment transfer capabilities. The key difference is that DemoGrasp uses a demonstration-editing approach with single-step RL to adapt a single trajectory across objects and embodiments, while D(R,O) Grasp employs a unified representation framework that directly models robot-object interaction through learned grasp prediction from hand descriptions and object point clouds.

Contributions Analysis

Overall novelty summary. DemoGrasp proposes learning universal dexterous grasping by editing a single demonstration trajectory—adjusting wrist pose for 'where' and joint angles for 'how'—then optimizing via RL across hundreds of objects. The paper resides in the Cross-Embodiment and Generalization Methods leaf, which contains only three papers total, indicating a relatively sparse research direction within the broader taxonomy. This leaf sits under Learning-Based Grasp Synthesis and Control, distinguishing itself from single-embodiment RL approaches and pure imitation learning branches by emphasizing transferability across diverse hand morphologies and object categories.

The taxonomy reveals neighboring leaves focused on Reinforcement Learning for Grasping (including Deep RL for Dexterous Manipulation and RL with Bionic Reflexes) and Human-Inspired Learning Approaches (covering Imitation Learning from Human Demonstrations and RL with Human Pose Priors). DemoGrasp bridges these areas: it starts from a human-like demonstration but formulates trajectory editing as a single-step MDP optimized via RL, rather than pure imitation or multi-step RL exploration. Nearby branches like Model-Based Grasp Planning and Specialized Grasping Tasks address complementary challenges—contact mechanics and task-specific scenarios—but do not emphasize the demonstration-editing paradigm central to this work.

Among 19 candidates examined, the DemoGrasp framework contribution shows 2 refutable candidates out of 8 examined, suggesting some prior work on demonstration-driven universal grasping exists within this limited search scope. The single-step MDP formulation encountered 1 refutable candidate from 1 examined, indicating at least one overlapping prior approach to trajectory editing or simplified action spaces. The vision-based sim-to-real transfer contribution found 0 refutable candidates among 10 examined, appearing more novel

within the sampled literature. These statistics reflect a top-K semantic search plus citation expansion, not an exhaustive survey, so additional relevant work may exist beyond the 19 papers analyzed.

Overall, the paper occupies a sparsely populated taxonomy leaf and introduces a demonstration-editing perspective that differs from mainstream multi-step RL or pure imitation paradigms. The limited search scope—19 candidates across three contributions—provides useful signals but cannot definitively rule out related work in adjacent research communities or recent preprints. The framework's novelty appears strongest in its sim-to-real transfer component, while the core demonstration-editing concept shows some overlap with prior efforts identified in the analysis.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: DemoGrasp framework for universal dexterous grasping via demonstration editing

Description: The authors introduce DemoGrasp, a framework that learns universal dexterous grasping policies by editing a single demonstration trajectory. The method changes wrist poses to determine where to grasp and hand joint angles to determine how to grasp, formulating trajectory editing as a single-step MDP optimized via RL with a simple reward combining binary success and collision penalty.

This contribution was assessed against **8 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Grasping Unknown Objects With Only One Demonstration
URL: View paper

Prior Art Analysis

Grasping Unknown Objects[56] demonstrates that prior work exists on learning dexterous grasping from a single demonstration. Both papers propose methods that start from one successful demonstration and adapt it to grasp novel objects. The candidate paper explicitly states it is 'a multifinger grasping learning method that requires only one demonstration' where 'a human remotely manipulates the robot via a wearable device to perform a successful grasping demonstration' which is then used as 'the initial reference trajectory for reinforcement learning training.' This directly parallels the original paper's claim of learning from 'a single demonstration trajectory' and using RL to adapt it. Both methods use RL to generate corrective actions to the demonstration, and both aim at universal/generalized grasping across diverse objects.

Evidence

Evidence 1 - **Rationale**: Both papers explicitly propose learning universal/generalized dexterous grasping from a single demonstration that serves as a reference trajectory for RL-based adaptation to novel objects. - **Original**: we proposedemograsp, a simple yet effective method for learning universal dexterous grasping. we start from a single successful demonstration of grasping a specific object and adapt to novel objects and poses by editing the robot actions in this demonstration - **Candidate**: we introduce a curriculum learning mechanism and propose a multifinger grasping learning method that requires only one demonstration. first, a human remotely manipulates the robot via a wearable device to perform a successful grasping demonstration. the state of the object and the robot is recorded ...

Evidence 2 - **Rationale**: Both papers share the core insight that a single demonstration can be modified/corrected via RL to achieve grasping across diverse objects, demonstrating prior work on demonstration editing for universal grasping. - **Original**: our key insight is that a single demonstration trajectory of grasping a specific object encodes many transferable patterns for universal grasping, such as approaching the object's grasp center, squeezing the hand pose, and lifting the wrist. to grasp various objects in different poses, we can slight... - **Candidate**: by combining robot proprioception and the point cloud features of the target object, a multimodal deep reinforcement learning agent generates corrective actions for the reference demonstration in the synergy subspace of grasping and trains in simulation environments.

Evidence 3 - **Rationale**: Both papers use RL in simulation to train policies that generalize across diverse objects by modifying/correcting a reference demonstration, establishing that this approach existed prior to the original paper's submission. - **Original**: we formulate this trajectory editing as a single-step markov decision process (mdp) and use rl to optimize a universal policy across hundreds of objects in parallel in simulation - **Candidate**: a multimodal deep reinforcement learning agent generates corrective actions for the reference demonstration in the synergy subspace of grasping and trains in simulation environments. meanwhile, considering the topological and geometric variations of different objects, we establish a learning curricu...

2. Deep Learning for Dexterous Robot Grasping
URL: View paper

Brief Assessment

Deep Dexterous Grasping[58] is a survey paper covering deep learning approaches for dexterous grasping broadly. It does not present a specific method for demonstration editing or trajectory adaptation, but rather reviews existing datasets, synthesis methods, and execution policies across the field. The candidate does not challenge the novelty of DemoGrasp's specific demonstration-editing framework.

3. Robotic grasping and fine manipulation
URL: View paper

Brief Assessment

Robotic Fine Manipulation[53] focuses on wrist compliance and force control for fine manipulation tasks, not on learning universal grasping policies via demonstration editing and reinforcement learning.

4. Learning Adaptive Dexterous Grasping from Single Demonstrations
URL: View paper

Brief Assessment

Adaptive Dexterous Grasping[54] focuses on learning multiple grasp skills from human demonstrations with trajectory following rewards and VLM-based skill selection, not on demonstration editing via SE(3) transformations and single-step MDP formulation as in DemoGrasp.

5. Learning object manipulation with dexterous hand-arm systems from human demonstration
URL: View paper

Brief Assessment

Learning From Demonstration[55] focuses on learning from human demonstrations using instrumented gloves and combines neural policies with online trajectory optimization, whereas DemoGrasp uses a single demonstration trajectory edited via RL in a single-step MDP formulation for universal grasping across diverse objects.

6. Universal Dexterous Functional Grasping via Demonstration-Editing Reinforcement Learning
URL: View paper

Prior Art Analysis

Universal Dexterous Grasping[51] demonstrates that a similar demonstration-editing framework for universal dexterous grasping was proposed prior to the original paper. Both papers use a single demonstration trajectory that is edited by modifying wrist poses (where to grasp) and hand joint angles (how to grasp). The candidate paper explicitly describes the same core mechanism: 'we collect one grasping demonstration and train a policy that outputs a wrist transformation (determining where to grasp) and a hand-style adaptation delta action (determining how to grasp). These actions edit the object-centric robot actions in the demonstration, which is then replayed for trial-and-error learning.' This directly parallels the original paper's claim of introducing DemoGrasp with demonstration editing.

Evidence

Evidence 1 - **Rationale**: Both papers describe the same core framework: using a single demonstration that is edited via wrist transformations and hand pose adjustments to achieve universal grasping across diverse objects. - **Original**: we proposedemograsp, a simple yet powerful framework for universal dexterous grasping that addresses these challenges. our key insight is that a single demonstration trajectory of grasping a specific object encodes many transferable patterns for universal grasping, such as approaching the object's g... - **Candidate**: we collect one grasping demonstration and train a policy that outputs a wrist transformation (determining where to grasp) and a hand-style adaptation delta action (determining how to grasp). These actions edit the object-centric robot actions in the demonstration, which is then replayed for trial-an...

Evidence 2 - **Rationale**: Both papers decompose the grasping problem into 'where to grasp' (wrist/affordance) and 'how to grasp' (hand pose/style), demonstrating the same conceptual framework for demonstration editing. - **Original**: for example, to grasp the same object at a different location, we can apply a transformation to the wrist poses in the trajectory, changingwhere to grasp; to grasp a larger object at the same position, we adjust the grasp poses to be more open, changinghow to grasp. in our method, the rl policy expl... - **Candidate**: we first decompose each functional grasping condition into two components:affordanceandgrasping style. the affordance specifies the region of the object to grasp (where to grasp), and the grasping style specifies the reference hand pose (how to grasp). they provide a complete description of the inte...

Evidence 3 - **Rationale**: Both papers formulate the task as a one-step MDP where the policy outputs transformation parameters to edit a demonstration, showing the same methodological approach. - **Original**: we formulate the demonstration-editing task as a single-step markov decision process (mdp). at each trial, given an arbitrary object placed at a random position, the policy outputs an se(3) transformation and delta hand joint angles, which are used to modify the end-effector poses and hand actions i... - **Candidate**: we formulate dexterous functional grasping as a one-step markov decision process (mdp) following yuan et al. [39]. under the state-based setting, the agent observes (sr,s o,x o,pafford,lstyle). here,s r denotes the robot end-effector 6d pose andso denotes the target object pose.xo represents the com...

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7. Learning Continuous Grasping Function with a Dexterous Hand from Human Demonstrations
URL: View paper

Brief Assessment

Learning Continuous Grasping[57] focuses on learning continuous grasping trajectories from human demonstrations using implicit functions and CV AE, not on demonstration editing via RL-based trajectory adaptation for universal grasping.

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8. An adaptive framework for manipulator skill reproduction in dynamic environments
URL: View paper

Brief Assessment

Adaptive Skill Reproduction[52] focuses on manipulator trajectory adaptation in dynamic environments with moving targets and unstable bases, not on universal dexterous grasping across diverse objects. The candidate uses a single demonstration for trajectory editing in dynamic scenarios, while the original paper addresses multi-fingered hand grasping across thousands of objects with RL optimization.

Contribution 2: Single-step MDP formulation with demonstration-editing action space

Description: The authors reformulate the grasping task as a single-step MDP where the policy outputs editing parameters (end-effector transformation and delta hand joint angles) that modify a demonstration trajectory. This compact action space and short horizon significantly reduce exploration challenges and eliminate the need for complex reward shaping used in prior methods.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Universal Dexterous Functional Grasping via Demonstration-Editing Reinforcement Learning
URL: View paper

Prior Art Analysis

Universal Dexterous Grasping[51] demonstrates prior use of the single-step MDP formulation with demonstration-editing action space. The candidate paper explicitly states it follows this approach: 'we formulate dexterous functional grasping as a one-step markov decision process (mdp) following yuan et al. [39]' and describes the same mechanism where 'the policy outputs an actiona = (∆t,∆q,k), where∆ t updates the end-effector pose, and∆q together with k modulates hand joint scaling.' This directly refutes the novelty claim, as the candidate paper uses the identical formulation of editing parameters (end-effector transformation and hand joint deltas) in a single-step MDP.

Evidence

Evidence 1 - **Rationale**: Both papers describe the same single-step MDP reformulation where demonstration editing is performed in one step, followed by replay and reward evaluation. - **Original**: mdp reformulation.given the grasp exploration scheme via demonstration editing, we reformulate the task as asingle-step mdp: the policy outputs a single action specifying the editing parameters, after which the edited demonstration is replayed in the environment for a maximum of t timesteps, and the... - **Candidate**: unlike conventional multi-step rl, which suffers from unstable optimization and high sample complexity in high-dof manipulation, our framework simplifies functional grasping into a one-step rl problem. we observe that grasp success and functional accuracy can be effectively optimized by editing a si...

Evidence 2 - **Rationale**: Both papers use the same action space structure: end-effector transformation (tee/∆t) and delta hand joint angles (∆qg/∆q), demonstrating identical formulation of the demonstration-editing action space. - **Original**: the action consists of the end-effector transformation tee and the delta hand grasp pose ∆qg used for demonstration editing. the transition replays the edited demonstration d′ and then terminates. - **Candidate**: the policy outputs an actiona = (∆t,∆q,k), where∆ t updates the end-effector pose, and∆q together with k modulates hand joint scaling coefficient relative to the target grasping style, conditioned on the object geometry.

Evidence 3 - **Rationale**: Both papers emphasize the same benefit of the single-step MDP formulation: reduced exploration challenges and improved sample efficiency through a compact action space. - **Original**: with the compact, low-dimensional action space and the short horizon introduced by the one-step mdp, the exploration challenge is significantly mitigated, making complicated reward engineering unnecessary. - **Candidate**: this formulation reduces the problem to a single-step rl task and tightly links the action space with the functional grasping conditions, leading to significantly improved sample efficiency.

Contribution 3: Vision-based sim-to-real transfer via flow-matching imitation learning

Description: The authors develop a sim-to-real transfer approach by training a flow-matching policy on successful rollouts from the learned RL policy with rendered camera images in simulation. This enables zero-shot deployment on real robots with various camera configurations (RGB and depth) and demonstrates strong generalization to spatial, background, and lighting changes.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. GENFLOWRL: Generative Object-Centric Flow Matching for Reward Shaping in Visual Reinforcement Learning
URL: View paper

Brief Assessment

GenFlowRL[65] focuses on using object-centric flow for reward shaping in RL, not sim-to-real transfer via flow-matching imitation learning for grasping policies with camera images.

2. Vfp: Variational flow-matching policy for multi-modal robot manipulation
URL: View paper

Brief Assessment

VFP[66] focuses on variational flow-matching for multi-modal action generation in manipulation tasks, not specifically on sim-to-real transfer for grasping. The candidate's sim-to-real approach uses variational inference and mixture-of-experts for multi-modality, which differs from the original paper's demonstration-editing framework for universal dexterous grasping.

3. DexVLG: Dexterous Vision-Language-Grasp Model at Scale
URL: View paper

Brief Assessment

DexVLG[63] uses flow-matching for grasp pose prediction aligned with language instructions, not for sim-to-real transfer of RL policies with camera images. The candidate focuses on vision-language-grasp modeling rather than transferring RL policies to real robots.

4. Maniflow: A general robot manipulation policy via consistency flow training
URL: View paper

Brief Assessment

ManiFlow[67] focuses on flow matching with consistency training for general manipulation across diverse robot setups, not specifically on sim-to-real transfer for grasping tasks. The original paper's contribution emphasizes zero-shot deployment with various camera configurations for dexterous grasping, while ManiFlow[67] addresses broader manipulation capabilities with different architectural innovations (dit-x, consistency training).

5. Graspvla: a grasping foundation model pre-trained on billion-scale synthetic action data
URL: View paper

Brief Assessment

GraspVLA[61] focuses on grasping tasks using billion-scale synthetic data with flow-matching for action generation, not on general RL frameworks for dexterous manipulation with demonstration editing as in the original paper.

6. Extremum Flow Matching for Offline Goal Conditioned Reinforcement Learning
URL: View paper

Brief Assessment

Extremum Flow Matching[62] focuses on offline goal-conditioned RL using flow matching for critic learning and trajectory planning, not on sim-to-real transfer for grasping. The real-world deployment uses teleoperated demonstrations directly on hardware rather than sim-to-real transfer from simulation-trained policies.

7. Genie Envisioner: A Unified World Foundation Platform for Robotic Manipulation
URL: View paper

Brief Assessment

Genie Envisioner[60] focuses on video generation and world modeling for robotic manipulation, not sim-to-real transfer for grasping tasks. The flow-matching component in Genie Envisioner[60] is used for action decoding from latent representations, not for vision-based imitation learning from simulation rollouts.

8. Flow as the Cross-Domain Manipulation Interface
URL: View paper

Brief Assessment

Flow Cross-Domain[59] uses object flow as a manipulation interface between human demonstrations and robot policies, not flow-matching for imitation learning. The original paper trains flow-matching policies on RL rollouts with rendered images, while the candidate uses flow for cross-domain transfer between human videos and simulated robot data.

9. Genflowrl: Shaping rewards with generative object-centric flow in visual reinforcement learning
URL: View paper

Brief Assessment

GenFlowRL Rewards[64] focuses on using object-centric flow for reward shaping in RL, not on sim-to-real transfer via flow-matching imitation learning for grasping policies as in the original paper.

10. Afforddexgrasp: Open-set language-guided dexterous grasp with generalizable-instructive affordance
URL: View paper

Brief Assessment

AffordDexGrasp[68] focuses on language-guided dexterous grasping using affordance representations and flow matching for affordance/grasp generation, not on sim-to-real transfer for general RL policies. The candidate's flow matching is used for different purposes (affordance and grasp generation) rather than distilling RL policies for sim-to-real transfer.

Appendix: Text Similarity Detection

Textual similarity detection checked 20 papers and found 3 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Universal Dexterous Functional Grasping via Demonstration-Editing Reinforcement Learning

Detected in: Contribution: contribution_1, Contribution: contribution_2

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

- [0] DemoGrasp: Universal Dexterous Grasping from a Single Demonstration View paper
- [1] A soft-robotic approach to anthropomorphic robotic hand dexterity View paper
- [2] Generalization of human grasping for multi-fingered robot hands View paper
- [3] Gamma: Generalizable articulation modeling and manipulation for articulated objects View paper
- [4] Grasp multiple objects with one hand View paper
- [5] Exploring Deep Learning Grasping Models with Soft Anthropomorphic Robotic Hands View paper
- [6] Grasp and dexterous manipulation of multi-fingered robotic hands: a review from a control view point View paper
- [7] Learning human-like functional grasping for multifinger hands from few demonstrations View paper
- [8] Dexterous manipulation for multi-fingered robotic hands with reinforcement learning: A review View paper
- [9] Design of a highly biomimetic anthropomorphic robotic hand towards artificial limb regeneration View paper
- [10] A new anthropomorphic robotic hand View paper
- [11] Grasp like humans: Learning generalizable multi-fingered grasping from human proprioceptive sensorimotor integration View paper
- [12] MagicHand: Context-Aware Dexterous Grasping Using an Anthropomorphic Robotic Hand View paper
- [13] Power grasp planning for anthropomorphic robot hands View paper
- [14] Model-based strategy for grasping 3D deformable objects using a multi-fingered robotic hand View paper
- [15] The developments and challenges towards dexterous and embodied robotic manipulation: A survey View paper
- [16] Learning from humans how to grasp: a data-driven architecture for autonomous grasping with anthropomorphic soft hands View paper
- [17] Tactile sensing soft fingertip with dual air bag structure for an anthropomorphic robotic hand View paper
- [18] Research on adaptive grasping with object pose uncertainty by multi-fingered robot hand View paper
- [19] A versatile robotic hand with 3D perception, force sensing for autonomous manipulation View paper
- [20] Toward human-like grasp: Functional grasp by dexterous robotic hand via object-hand semantic representation View paper
- [21] Soft-Grasping With an Anthropomorphic Robotic Hand Using Spiking Neurons View paper
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