ProHand: The Future of Humanoid Manipulation

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March 2025

Abstract: Humanoid robots will lead to the greatest value-add in the history of humanity. One value proposition of humanoid robots is to automate complex physical tasks across industries. With 99.5% of civilian jobs requiring fine hand manipulation [1], achieving human-level dexterity is critical for widespread humanoid adoption. Recent AI advances now make solving these manipulation challenges feasible, though current humanoid hand capabilities remain limited.

We present an integrated approach combining optimized hardware design, systematic data collection, and advanced AI to develop highly dexterous humanoid hands. Our solution balances key performance factors and introduces a five-level classification framework for robotic dexterity, establishing benchmarks toward achieving fully autonomous manipulation capabilities.

1 Introduction

The future of humanity is automated, and humanoid robots are the crown jewel of automation. Achieving human-level hand dexterity is essential for widespread humanoid adoption, as 99.5 % of civilian jobs require fine hand manipulation [1]. Current approaches to robotic hand development fall short of real-world requirements.

In this whitepaper, we present a novel benchmark for robotic dexterity and present three components of our integrated approach: optimized hardware design, systematic data collection, and advanced AI learning systems. Our approach lays a clear path toward achieving the dexterity required for humanoids to transform industries through autonomous physical manipulation.

2 Benchmarking Dexterity

To better define and track progress in robotic hand dexterity, we classify manipulation capabilities into five levels:

Level 1	Level 2	Level 3	Level 4	Level 5
Infant	Toddler	Child	Adolescent	Adult
0-12 months	1-3 years	4-7 years	8-17 years	18+ years

Figure 6: Developmental stages of manipulation capabilities

1) **Level 1** - Infant (0-12 months): Basic Grasping and Releasing
    - *Capabilities:* Simple grasp and release, unable to operate autonomously.
    - *Robot Comparison:* Pick-and-place robots requiring full human control.
    - *Technical Requirements:* Basic force control, primitive object recognition.
    - *Current Examples:* Industrial grippers, simple prosthetic hands.
2) **Level 2** - Toddler (1-3 years): Emerging Dexterity and Autonomy
    - *Capabilities:* Basic in-hand manipulation, early bi-lateral skills, minimal cognitive ability.
    - *Robot Comparison:* Assembly robots handling rigid objects with some reorientation.
    - *Technical Requirements:* Multi-finger coordination, basic tactile feedback, simple task planning.
3) **Level 3** - Early Childhood (4-7 years): Developing Fine Motor Skills
    - *Capabilities:* Basic tool use, some autonomous operation, early force regulation.
    - *Robot Comparison:* Autonomous robots sorting rigid and soft objects.
    - *Technical Requirements:* Advanced tactile sensing, object property recognition, tool manipulation.
4) **Level 4** - Adolescence (8-17 years): Refined Dexterous Motor Skills
    - *Capabilities:* Complex bi-manual dexterity, adapting to different situations.
    - *Robot Comparison:* Robots capable of long-term tasks, requiring explicit instructions.
    - *Technical Requirements:* Multi-modal sensing integration, advanced learning systems, generalization to novel objects.
    - *Current Examples:* Research prototypes only, no commercial systems.
5) **Level 5** - Adulthood (18+ years): Peak Dexterity and Adaptability

- *Capabilities:* Mastery of fine motor skills, real-time adaptability without prior training.
- *Robot Comparison:* Fully autonomous humanoids capable of safely operating with humans and executing long-term tasks without explicit guidance.
- *Technical Requirements:* Human-level tactile perception, advanced cognitive models, real-time adaptation to novel situations.
- *Current Examples:* No existing systems at this level.

This classification system provides a clear framework for evaluating the current state of robotics and setting measurable goals for future development. To push humanoid dexterity to higher levels, we focus on three key areas: hardware, data collection, and AI integration.

3 Hardware

Hands represent the most sophisticated and essential manipulation tools in the human body, enabling everything from precise surgical procedures to creative artistic expression. According to the U.S. Bureau of Labor Statistics [1], over 99.5% of occupations, ranging from bartenders, to engineers, to pharmacists, require advanced manual dexterity. This highlights how critical our hands are to human productivity. Therefore, for humanoid robots to achieve true utility and autonomy, developing advanced robotic hands is paramount.

3.1 Current Hardware Limitations

Despite how hands are a cornerstone of human productivity, current robotic hand designs face significant limitations in matching human capabilities. In a recent Science paper, "the size and strength of current robotic hands often exceed the size and weight of the objects they are designed to handle" [2]. This fundamental mismatch between hand and object dimensions creates immediate practical challenges for robotic manipulation.

Additionally, most hands today essentially act as glorified claw grippers, with fingers only able to close in a singular tight grip and unable to manipulate obejcts once held [2].

Furthermore, with a lack of tactile sensing, robotic hands barely perform tasks seemingly trivial to humans such as lifting a sheet of paper or gripping a handle. More intricate tasks like turning a key or lifting a phone are far beyond the capabilities of current robotic hands [2].

Building on these observations, we identify four critical challenges:

- **Durability:** Existing hands break down quickly under regular use, with mean time between failures often measured in minutes and hours rather than days [3].
- **Strength:** Insufficient grip force for handling diverse objects, with most advanced dexterous hands providing less than 30% of human grip strength while requiring significantly more power [4].
- **Form Factor:** Designs are either too heavy, too large, or deviate far from human hand anatomy, limiting their ability to operate in environments designed for humans [5].
- **Dexterity:** Most hands lack human-level fine motor control, with limited degrees of freedom and inadequate tactile sensing capabilities [6].

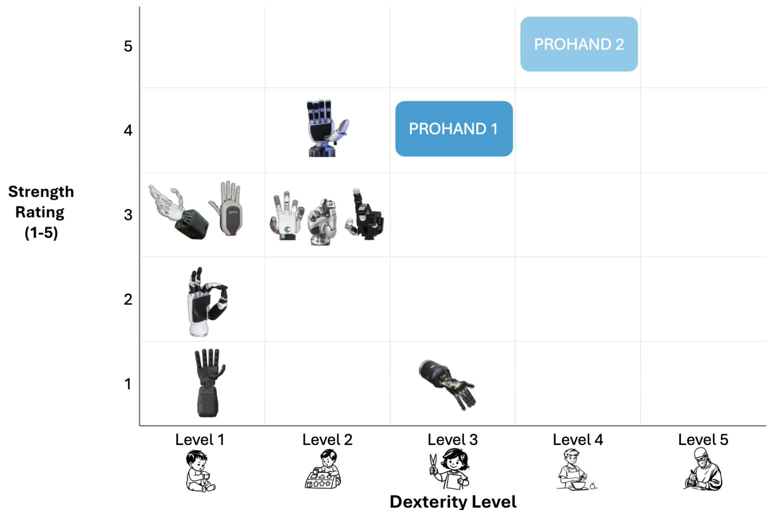

Figure 7: Comparison of robotic hand strength vs. dexterity levels.

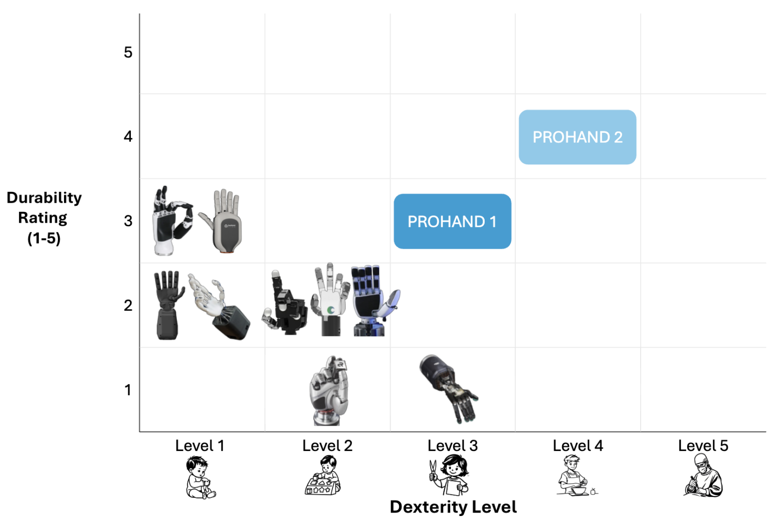

Figure 8: Durability vs. dexterity tradeoff in robotic hands.

Hand Name	**Dexterity Level**	**Durability Rating**	**Strength Rating**
Allegro Hand	2	2	3
Shadow Hand	3	1	1
Dexhand	1	3	3
Inspire Robot Hand	1	3	4
Seed Adult Robot Hand	1	3	1.5
Agile Robots Agile Hand	2	4	3
Mimic Robot Hand	1	2	3
Robotera X-Hand	2	3	4
Tesollo DG-5F Robot Hand	2	2	3
ProHand 1	3	3	4
Prohand 2	**4**	**4**	**5**

Table 1: Comparison of Current Robotic Hands (Scale: 1-5, where 5 represents the highest performance)

The data in Table 1 reveals a critical challenge in current robotic hand development: significant tradeoffs between key performance metrics. For instance, the Shadow Hand, which achieves the highest dexterity rating among commercial hands, suffers from poor durability and strength ratings. This pattern is common across the industry - hands designed for high dexterity often sacrifice reliability and power, while more robust designs typically lack the fine motor control needed for complex manipulation tasks. These tradeoffs highlight why achieving human-level dexterity remains an elusive goal, as no current solution successfully balances all critical performance factors.

3.2 Developing Our Own Hardware

Given these limitations, we have chosen to develop our own robotic hand hardware to solve the manipulation problem effectively. Our product, ProHand, prioritizes:

- A balance of durability, strength, form factor, and dexterity to create a versatile, high-performance hand.
- Advanced material and actuator selection for improved robustness and lifespan.
- Custom tendon-driven mechanisms to enable natural hand movements and force control.
- Wearable skin sensors to measure and collect tactile data.

Our hardware design focuses on creating hands that can effectively interact with environments designed for humans while maintaining durability in real-world applications. This approach enables our humanoids to utilize existing tools and perform tasks in human environments without requiring specialized equipment or modifications.

4 Data

Our key philosophy is that data collection is one of the biggest bottlenecks in robotic learning. Traditional teleoperation methods are extremely inefficient in terms of scaling data and consuming capital.

4.1 Limitations of Current Approaches

The most common practice for data collection in this industry is teleoperation, which faces several critical limitations:

- **Hardware Constraints:** Most research groups have access to very few humanoid platforms (typically fewer than 100 units).
- **Economic Inefficiency:** Humanoids are expensive to build and operate solely for data collection purposes.
- **Time Inefficiency:** Teleoperation is cumbersome and significantly slower than natural human movement. Research from DexHub [7] indicates that teleoperation-based data collection typically yields only 5-10 demonstrations per hour, severely limiting dataset scale.
- **Skill Transfer Challenges:** Human operators must adapt their natural movements to the constraints of the robot, creating a mismatch between human intent and robot execution.

These limitations make teleoperation-based data collection a brute-force approach that is unsustainable for developing truly dexterous systems at scale. Overall, we believe tele-operation based data collection is a new form of brute-force and it's extremely inefficient for capital and time.

4.2 Our Integrated Approach

Our unique hand design includes wearable skin sensors, which enabled a much more efficient data collection scheme. Data will be collected by human operators only, without constraints of humanoids. As shown in Figure 9, operators will wear HD cameras on their head and sensor gloves as they do their jobs. Their hand pose, tactile feedback, and their field of view videos will be logged. Our data strategy can be summarized as follows:

- Developing scalable data collection methodologies that minimize the need for expensive human teleoperation.
- Leveraging simulation environments to generate high-quality training data efficiently.
- Integrating real-world sensor feedback to continuously refine and improve manipulation performance.
- Avoiding brute-force teleoperation, which relies on expensive robots and multiple shifts of operators, making it unsustainable for large-scale data collection.

This approach allows us to collect orders of magnitude more data than traditional methods, enabling more robust training of our AI models and accelerating the development of advanced manipulation capabilities.

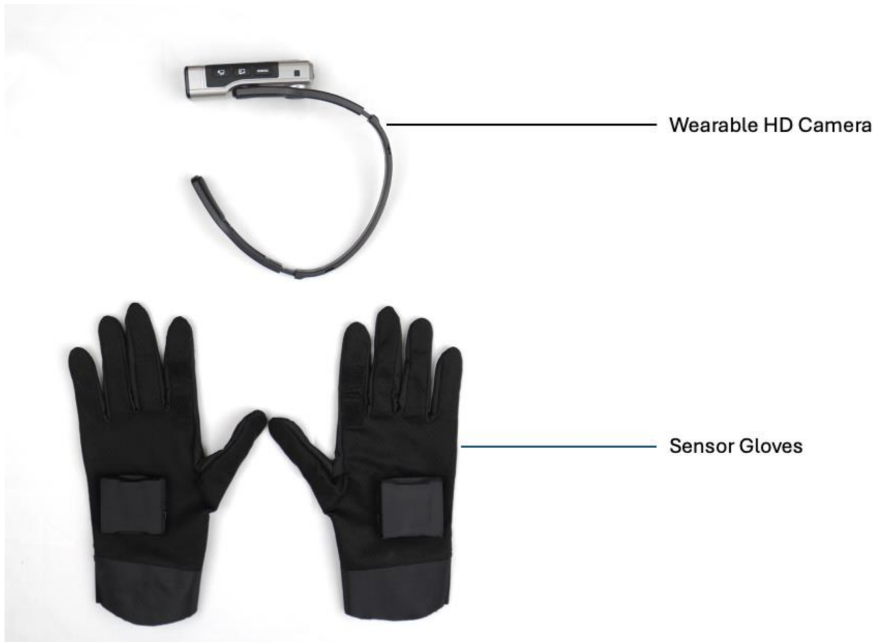

Figure 9: Wearable HD camera and sensor gloves for human demonstration data collection.

5 AI

The core of our AI system revolves around seamlessly integrating human tactile intuition with robotic dexterity. Our approach leverages a dual-glove system—one pair for a human operator and another for a robotic counterpart—each embedded with high-fidelity tactile and position sensors. This setup enables real-time data acquisition of human tactile interactions, forming the basis for an advanced learning model that optimizes the robotic hand's actuation.

AI components are deeply embedded within our development roadmap, structured into four key areas:

5.1 Foundational Lower Cortex Model - Tactile-Actuation Learning Loop

By capturing rich tactile data from human demonstrations, our AI models learn the complexities of touch, grip force modulation, and dynamic adaptation to various objects and surfaces. This enables the generalization of learned behaviors to previously unseen objects, forming a foundational model for dexterous in-hand manipulation.

- The collected data is used to train neural networks that map sensor inputs to precise actuator responses. This ensures the high DOF tendon-driven robotic hand achieves high precision with human-like dexterity
- Reinforcement Learning (RL) techniques further refine the control policies by minimizing errors and enhancing adaptability to novel interaction

- Additional vision data, combined with large language models (LLMs) allow for scenario labeling, task identification, and contextual reasoning. The key characteristics of each interaction are tokenized and leveraged as modulation parameters to adjust grasping behavior dynamically.

5.2 Digital Twin - Closing Gap between Simulation and Real Hardware

- A critical aspect of our AI framework involves leveraging real-world tactile data to bridge the disparity between simulated models and physical hardware performance. This includes modeling hardware variability to refine the distribution of disturbed parameters.
- By continuously integrating feedback from real-world interactions, our self-improving models refine simulation parameters and control strategies, ensuring greater alignment with physical execution.
- This approach enhances predictive accuracy and improves robotic performance, making the system more robust to variations in hardware build.

5.3 AI Agent – Profession-specific Dexterity Fine-Tuning

- By collecting the operational data from specific professional fields, we refine our foundational model while also enabling fine-tuned applications for specialized roles for our customers.
- We develop personalized AI agents that tailor robotic dexterity to industry-specific requirements, ensuring optimal adaptation for various use cases, from surgical precision to industrial manipulation
- This approach enables a seamless transition from generalized learning to highly customized robotic behavior for end-user applications

5.4 AI-driven Generative Design

- Beyond optimizing control policies, we leverage AI-driven generative design techniques to accelerate the permutation of the robotic hand design to enhance the physical structure and performance.
- This involves using the digital twin model and foundational control policy to expedite the design space exploration in simulation, reducing the physical design iteration and shortens the design-to-deployment timeline.

By integrating advanced AI methodologies across learning, simulation, professional adaptation, and generative design, our system pioneers a new paradigm in human-inspired robotic dexterity. Our approach not only enhances real-world robotic interaction but also accelerates the evolution of robotic hands toward unprecedented levels of adaptability and efficiency.

6 Conclusion

Achieving Level 5 dexterity is critical for humanoids to reach their full potential. The recent breakthroughs in AI and robotics provide a strong foundation for rapid advancements in this field. With focused development, humanoids will revolutionize industries by performing complex tasks that currently require human hands. Our proprietary hardware, data, and AI-driven approach will be key enablers in bridging the gap between existing robotic hands and the dexterity required for true humanoid autonomy.

The integrated approach we have outlined—combining innovative hardware design, efficient data collection methodologies, and advanced AI systems—creates a comprehensive framework for developing humanoid hands with unprecedented capabilities. By addressing the fundamental challenges of balancing durability, strength, form factor, and dexterity, we establish a path toward achieving fully autonomous humanoid operation.

Our classification system provides a clear roadmap for progress, enabling objective assessment of current capabilities and setting measurable goals for future development. As we continue to advance through these levels of dexterity, we move closer to realizing the full potential of humanoid robots in transforming industries and enhancing human capabilities.

References

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