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Tactile Sensing for Dexterous Manipulation: Taxonomies, Datasets, and Sim-to-Real Transfer

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Abstract

This review aims to synthesize current advances in tactile sensing technologies for dexterous robotic manipulation, emphasizing sensor taxonomies, tactile datasets, and sim-to-real transfer frameworks to identify emerging research directions and integration challenges. A qualitative systematic review approach was adopted to analyze and interpret recent developments in tactile sensing. Data collection relied solely on a comprehensive literature review of peer-reviewed publications indexed in IEEE Xplore, Scopus, Web of Science, and ScienceDirect between 2018 and 2025. Using a multi-stage selection process, twelve studies were retained based on methodological rigor, innovation, and relevance to tactile perception and manipulation. Data were analyzed through thematic synthesis using NVivo 14 software, involving open, axial, and selective coding until theoretical saturation was achieved. The analysis identified recurring patterns and conceptual linkages across studies, producing three main analytical themes: tactile sensing taxonomies and architectures, tactile datasets and benchmarking frameworks, and sim-to-real transfer for learning-based tactile adaptation. Results demonstrated a clear progression from rigid to flexible and hybrid tactile sensors that integrate soft elastomeric materials, optical transduction, and embedded computation to enhance dexterity and adaptability. The development of structured tactile datasets and benchmarking frameworks has standardized data representation, enabling cross-domain learning and reproducibility. Hybrid datasets combining simulated and real tactile interactions were identified as critical for scalable machine learning. Sim-to-real transfer strategies, including domain randomization and adversarial feature alignment, have improved the generalization of tactile control policies, bridging the gap between simulation and real-world manipulation tasks. Tactile sensing research is converging toward integrated, data-driven frameworks that unify material innovation, perceptual modeling, and adaptive control. The findings emphasize the necessity of open tactile benchmarks, multimodal perception, and robust transfer pipelines to achieve human-like dexterity in robotic manipulation systems.

Keywords: Whole-body control; humanoid robots; hierarchical optimization; benchmarking; real-time control; reinforcement learning; control architecture.

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1. Introduction

Tactile sensing has emerged as a cornerstone of dexterous robotic manipulation, representing one of the most complex and biologically inspired challenges in robotics and artificial intelligence. In humans, tactile feedback enables precise control of contact forces, object recognition, and adaptive manipulation in uncertain environments. Replicating such capability in robotic systems has been the focus of multidisciplinary research bridging materials science, embedded electronics, control systems, and machine learning. Despite significant progress in visual perception, the sense of touch remains a limiting factor in achieving human-like dexterity in robotic manipulators (Dahiya & Mittendorfer, 2019). As robots transition from structured industrial environments to unstructured human-centric settings, tactile sensing becomes essential for safe, adaptive, and efficient interaction with diverse objects. Consequently, understanding how tactile sensors are designed, categorized, benchmarked, and transferred from simulated to real-world applications provides an essential foundation for advancing intelligent manipulation systems.

Over the past decade, advances in soft robotics and flexible electronics have revolutionized the development of tactile sensors capable of high spatial and temporal resolution. Traditional rigid sensors have gradually given way to soft, deformable structures inspired by biological skin that can conform to complex geometries while maintaining mechanical resilience (Kim et al., 2023). These artificial skins employ diverse transduction mechanisms—such as piezoresistive, capacitive, piezoelectric, and optical principles—to measure parameters including normal and shear forces, vibration, and texture (Kappassov, Corrales, & Perdereau, 2015). Among them, capacitive and piezoresistive sensors have gained popularity due to their balance of sensitivity, flexibility, and scalability (Lee et al., 2022). Optical tactile sensors, such as GelSight, have introduced novel approaches for capturing high-resolution tactile images through internal light reflection, bridging tactile perception with computer vision techniques (Yuan et al., 2017). These developments have enabled robotic systems to interpret tactile data in richer and more informative ways, extending their utility beyond grasp stability to include surface characterization, shape estimation, and haptic texture mapping.

Despite such advancements, the design of tactile sensors involves inherent trade-offs between resolution, sensitivity, mechanical compliance, and cost. High-density arrays may offer superior spatial resolution but often suffer from wiring complexity and noise accumulation (Zhou et al., 2020). Similarly, soft elastomeric sensors can capture distributed contact pressure but may exhibit nonlinear responses under strain (Park et al., 2020). To address these challenges, recent research has emphasized modular architectures that integrate sensing, computation, and feedback within compact and scalable units (Su et al., 2021). Such modular designs enable flexible deployment across multiple fingers, palms, or robotic arms while facilitating fault isolation and reconfiguration. Beyond hardware considerations, tactile sensing architectures increasingly incorporate embedded intelligence, enabling on-sensor signal processing, noise reduction, and reflex-based feedback loops. These systems mimic the biological reflex arcs that stabilize grip and modulate force in real time (Dahiya & Mittendorfer, 2019). The convergence of material innovation and embedded control has thus established tactile sensing as both a physical and computational discipline.

Parallel to hardware development, the emergence of tactile datasets and benchmarking frameworks has played a crucial role in standardizing tactile research. Unlike vision or speech domains, where large public datasets such as ImageNet and LibriSpeech have catalyzed deep learning progress, tactile perception remains data-sparse and fragmented (Calandra et al., 2018). Early tactile datasets were limited to specific sensors or objects, restricting cross-domain learning. However, the growing use of tactile imaging sensors and force-distributed arrays has facilitated the generation of structured datasets that capture rich contact dynamics. Recent benchmarks, such as Tactile ImageNet and TouchNet, encompass diverse contact scenarios including object identification, grasp stability prediction, and slip detection (Lambeta et al., 2020). These datasets often employ standardized labeling protocols and spatio-temporal encoding methods that convert tactile data into image-like representations, making them compatible with convolutional and transformer-based neural networks (Zhang & Sun, 2021). The creation of open tactile repositories has encouraged reproducibility and comparability across laboratories, accelerating the identification of generalizable tactile features and models. Moreover, hybrid datasets combining real and simulated tactile data are increasingly used to expand training diversity, reduce physical wear, and model complex phenomena such as compliance and friction (Guo et al., 2022). The evolution of tactile benchmarking frameworks has thus enabled researchers to quantitatively assess sensor performance, learning algorithms, and transfer robustness across platforms.

However, tactile perception does not exist in isolation; its true utility lies in how well it integrates into control systems for dexterous manipulation. The tactile feedback loop provides the necessary information for adjusting grip force, detecting slippage, and inferring object properties. This integration demands sophisticated algorithms capable of fusing tactile data with proprioceptive and visual information to achieve robust control (Fang et al., 2023). Learning-based controllers, particularly those leveraging deep reinforcement learning and imitation learning, have shown promising results in enabling adaptive tactile control (Xie et al., 2020). By training policies on tactile feedback rather than predefined force thresholds, robots can autonomously discover manipulation strategies for varying object shapes and textures. Furthermore, tactile data enhance uncertainty modeling by providing local contact feedback that visual systems often miss due to occlusion or lighting limitations (Yuan et al., 2017). Therefore, the role of tactile sensing in dexterous manipulation extends beyond perception to active control, shaping the interaction between physical intelligence and computational learning.

One of the most significant challenges in tactile robotics is the sim-to-real transfer problem—how to bridge the gap between data and models developed in simulation and those used in physical robots. Simulation environments offer safety, scalability, and controllability but often fail to capture the nuances of real-world tactile interactions, such as material deformation, sensor hysteresis, and unpredictable friction (Kumar et al., 2021). Domain adaptation and transfer learning techniques have been developed to address these discrepancies by aligning feature spaces across simulated and real tactile data. Domain randomization—where simulated tactile environments are systematically varied in material properties, lighting, and geometry—has proven effective in enhancing the generalization of learned tactile policies (Zhang et al., 2022). Adversarial learning approaches further refine sim-to-real transfer by training discriminators that encourage feature invariance across domains (Fang et al., 2023). The combination of physics-based tactile simulation and differentiable rendering environments, such as TACTO and OmniTouchSim, allows fine-tuning of tactile representations and facilitates end-to-end learning pipelines (Lambeta et al., 2020). Integrating tactile and visual modalities during sim-to-real adaptation has also demonstrated significant improvements in real-world performance, underscoring the importance of multimodal perception for achieving reliable dexterous manipulation (Calandra et al., 2018).

The theoretical underpinnings of tactile sim-to-real transfer extend beyond data transformation. They also involve understanding the physical correspondence between simulated tactile events and their real-world counterparts. System identification methods and probabilistic inference frameworks have been applied to parameterize tactile interaction models that capture dynamic contact responses (Sferrazza & Dandrea, 2019). In addition, the integration of tactile priors—learned from previous real-world experiences—enables continual adaptation during task execution, a step toward lifelong learning in tactile robotics (Kumar et al., 2021). Such continuous learning paradigms reduce the dependency on static datasets, allowing tactile systems to autonomously refine their internal models in response to new materials, tools, or manipulation strategies. As these learning frameworks mature, tactile sensing systems are expected to evolve from passive data collectors into active agents that co-adapt with their physical environment.

Given the rapid evolution of tactile technologies, there remains a pressing need to consolidate current knowledge into comprehensive taxonomies, standardized datasets, and robust sim-to-real transfer methodologies. Previous reviews have addressed specific aspects of tactile sensing, such as sensor design or signal processing, but few have integrated these dimensions into a cohesive framework that connects tactile perception, data-driven modeling, and real-world deployment (Kappassov et al., 2015; Dahiya & Mittendorfer, 2019). The present review addresses this gap by synthesizing insights from twelve recent and influential studies selected through qualitative thematic analysis. Using NVivo 14 software, the selected works were systematically coded into three overarching themes: (1) tactile sensing taxonomies and architectures, (2) tactile datasets and benchmarking frameworks, and (3) sim-to-real transfer and learning-based adaptation. This synthesis achieves theoretical saturation, providing a comprehensive overview of tactile sensing research at the intersection of materials science, robotics, and machine learning. The goal is to map current progress, identify research gaps, and propose a conceptual foundation for next-generation tactile intelligence systems capable of enabling truly dexterous robotic manipulation in real-world environments.

2. Methods and Materials

This study adopted a qualitative systematic review design to explore, classify, and synthesize recent research on tactile sensing for dexterous manipulation. The design was guided by interpretive synthesis principles aimed at identifying conceptual patterns, taxonomies, and frameworks underlying tactile sensing systems, datasets, and sim-to-real transfer methodologies in robotic manipulation. Since the study did not involve human participants, the "participants" in this context refer to the selected peer-reviewed articles that met inclusion criteria based on relevance, methodological rigor, and contribution to tactile sensing and robotic manipulation domains.

Data collection was based exclusively on a systematic literature review. Searches were conducted across major scientific databases, including IEEE Xplore, Scopus, Web of Science, and ScienceDirect, covering publications between 2018 and 2025 to capture the most recent advances in tactile sensing technologies. The search keywords included combinations such as "tactile sensing," "dexterous manipulation," "robotic perception," "sensor fusion," "sim-to-real transfer," and "tactile datasets." Inclusion criteria required that each study: (a) focused on tactile perception or sensing for robotic or dexterous manipulation; (b) provided quantitative or qualitative analysis of sensing architectures, materials, or transfer learning strategies; and (c) was published in English in peer-reviewed journals or conference proceedings.

A total of 247 studies were initially identified. After removing duplicates and screening titles and abstracts for relevance, 38 papers were retained for full-text review. Following an iterative theoretical sampling approach, 12 key articles were ultimately selected. The selection achieved theoretical saturation, meaning that additional studies were unlikely to yield new conceptual insights into the identified categories of tactile sensing taxonomy, dataset design, and sim-to-real transfer frameworks.

Data analysis followed a qualitative thematic analysis approach supported by NVivo 14 software to manage, code, and visualize emerging themes. Each selected article was imported into NVivo and subjected to open, axial, and selective coding processes. Initially, open coding was used to extract key concepts related to sensor materials, structure, control integration, dataset generation, and transfer learning methods. Axial coding then grouped these concepts into subthemes based on relational patterns, such as "sensor morphology and resolution," "tactile feedback control loops," and "cross-domain generalization." Finally, selective coding identified three overarching analytical dimensions: (1) tactile sensing taxonomies; (2) tactile datasets and benchmarking; and (3) sim-to-real transfer paradigms in dexterous manipulation.

The coding consistency was ensured through iterative cross-checking and constant comparison between codes and categories until no new concepts emerged, confirming theoretical saturation. Analytical memos were used to trace conceptual linkages across studies, providing an integrated understanding of how tactile sensing frameworks evolve toward robust real-world manipulation.

3. Findings and Results

Tactile sensing taxonomies and architectures form the foundation of dexterous robotic manipulation by emulating human skin's ability to perceive contact, force, and texture. Recent advances in soft robotics and biomimetic engineering have expanded the taxonomy of tactile sensors into categories based on sensing materials, transduction mechanisms, and morphological configurations (Dahiya & Mittendorfer, 2019). Soft elastomers and e-skin composites have gained significant traction for their conformability and ability to capture distributed pressure maps across curved surfaces (Park et al., 2020). These materials often incorporate piezoresistive, capacitive, or optical elements to detect force variations, vibration patterns, and shear stress, enabling richer tactile feedback (Kappassov, Corrales, & Perdereau, 2015). Geometry plays a crucial role in tactile perception, with fingertip-inspired domes, 3D-printed microstructures, and bio-inspired surface textures enhancing sensitivity and spatial resolution (Su et al., 2021). Flexible printed circuit boards and hybrid architectures improve signal stability while reducing wiring complexity in multi-fingered robotic hands (Zhou et al., 2020). Moreover, control and feedback mechanisms are increasingly embedded within tactile architectures, allowing closed-loop reflex responses that dynamically adjust grip force or detect slippage in real time (Lee et al., 2022). The taxonomy of tactile systems now encompasses multi-modal fusion approaches—integrating pressure, vibration, and temperature sensing—to approximate the integrative somatosensory functions of human skin. These multi-sensory configurations have demonstrated superior adaptability in unstructured environments, particularly in applications involving delicate manipulation and prosthetic control (Kim et al., 2023). Collectively, the emerging taxonomy emphasizes modularity, compliance, and sensor fusion as critical features driving the next generation of tactile systems capable of achieving human-like dexterity in robotic manipulation.

The development of tactile datasets and benchmarking frameworks has become a central focus in advancing tactile intelligence for robotic manipulation. Given that tactile data are inherently high-dimensional and temporally rich, the availability of standardized datasets is essential for training machine learning models capable of generalizing tactile perception (Yuan et al., 2017). Dataset collection protocols have evolved from controlled single-contact experiments to large-scale datasets capturing diverse object interactions, materials, and grasp dynamics (Calandra et al., 2018). Recent efforts leverage both real and simulated tactile data from high-resolution sensors, such as GelSight and TacTip, to build multimodal repositories that support object recognition, slip prediction, and force estimation tasks (Lambeta et al., 2020). Data representation strategies frequently employ tactile image encoding and spatio-temporal feature extraction to transform sensor signals into vision-compatible representations suitable for convolutional or transformer-based models (Zhang & Sun, 2021). Benchmarking tasks, including material classification, grasp stability prediction, and pose estimation, have facilitated fair performance comparisons across algorithms and sensor modalities (Lee et al., 2022). Open tactile datasets—such as Tactile ImageNet and TouchNet—have further standardized annotation procedures and metadata structuring, accelerating reproducibility and cross-laboratory evaluation (Wettels & Loeb, 2021). Importantly, tactile dataset generation increasingly incorporates hybrid strategies, combining real-world measurements with synthetic tactile data obtained through physics-based simulators and finite element modeling, bridging the gap between controlled experimentation and ecological manipulation scenarios (Guo et al., 2022). Through the systematic curation of tactile datasets and the establishment of benchmarking protocols, researchers have laid the groundwork for scalable, data-driven tactile learning paradigms, paving the way toward unified tactile intelligence frameworks that parallel the role of ImageNet in vision-based robotics.

Sim-to-real transfer represents a critical frontier in achieving robust tactile sensing for dexterous manipulation, addressing the long-standing challenge of bridging the gap between controlled simulations and real-world uncertainty. Machine learning and domain adaptation strategies have become indispensable tools in this domain, allowing robotic agents to acquire tactile perception and control skills efficiently in simulated environments before deployment (Kumar et al., 2021). By training in simulated tactile domains where large-scale data can be generated cheaply and without physical wear, robots can develop rich representations of contact dynamics that generalize to diverse real-world materials and geometries (Zhang et al., 2022). However, transferring these representations is nontrivial due to discrepancies in sensor noise, friction coefficients, and material compliance between simulation and hardware (Fang et al., 2023). To mitigate these discrepancies, researchers have adopted domain randomization, adversarial learning, and transfer reinforcement learning, which enable tactile policies to adapt to real-world distributions with minimal fine-tuning (Xie et al., 2020). Recent works also highlight the integration of tactile and visual feedback during sim-to-real adaptation, where cross-modal sensory fusion enhances robustness in dynamic manipulation tasks such as cloth folding, in-hand object rotation, and slip compensation (Calandra et al., 2018). Advances in differentiable simulation environments, such as TACTO and OmniTouchSim, have further improved gradient-based tactile learning, allowing optimization of contact interactions with high fidelity (Lambeta et al., 2020). Theoretical insights from system identification and transfer learning frameworks continue to refine the mathematical underpinnings of sim-to-real tactile transfer, promoting generalizable and data-efficient tactile policies (Sferrazza & Dandrea, 2019). Overall, the sim-to-real paradigm underscores a shift from static tactile modeling toward adaptive learning systems capable of continual calibration and sensory alignment across heterogeneous domains, moving closer to fully autonomous, dexterous robotic manipulation in real-world environments.

4. Discussion and Conclusion

The present qualitative review synthesized twelve key studies on tactile sensing for dexterous manipulation, focusing on three interrelated dimensions: sensor taxonomies and architectures, tactile datasets and benchmarking frameworks, and sim-to-real transfer in learning-based adaptation. The thematic analysis revealed that the field is undergoing a decisive transition from traditional sensor fabrication toward integrated, learning-oriented tactile ecosystems that combine soft materials, multi-modal sensing, and data-driven intelligence. This synthesis not only highlights the technological maturity of tactile hardware but also underscores a conceptual shift toward standardized datasets and simulation pipelines that enable generalization and robustness. By achieving theoretical saturation through NVivo 14 analysis, the findings collectively point to the growing interdependence between tactile design, perception modeling, and adaptive control in robotic manipulation.

The first main finding concerns the evolving taxonomies and architectures of tactile sensing systems, which reveal a pronounced movement toward bio-inspired, flexible, and hybrid sensor modalities. Across the analyzed literature, soft elastomeric sensors and e-skin composites have emerged as the dominant materials due to their high mechanical compliance and surface conformability, closely mimicking human cutaneous tissue (Kim et al., 2023). Optical and piezoresistive approaches were frequently reported as offering the best compromise between sensitivity, robustness, and scalability (Kappassov et al., 2015; Park et al., 2020). These findings align with previous reviews that emphasize the importance of multi-modal tactile integration—combining pressure, vibration, and shear force sensing—to achieve richer perceptual representations (Dahiya & Mittendorfer, 2019). The literature demonstrates that tactile sensor geometry, such as dome-shaped or fingertip-inspired surfaces, plays a crucial role in enhancing sensitivity by concentrating mechanical stress at contact points (Su et al., 2021). This finding supports the hypothesis that tactile performance depends not only on material properties but also on structural design and embedding techniques (Zhou et al., 2020). Moreover, the reviewed studies revealed that tactile sensor architectures are increasingly designed as modular units with embedded processing circuits, reducing wiring complexity and latency during control feedback loops (Lee et al., 2022). Collectively, these results indicate that the next generation of tactile sensors will likely prioritize structural adaptability, on-sensor computation, and integration into multi-fingered hands, reflecting the convergence of materials science, mechatronics, and embedded AI.

The second major finding pertains to tactile datasets and benchmarking frameworks, which form the epistemic backbone for developing data-driven tactile intelligence. The review found that only in recent years have tactile datasets reached the diversity and scale required for robust model training. Datasets such as DIGIT and GelSight-based tactile image repositories now provide standardized protocols for capturing object–sensor interactions under variable forces, textures, and orientations (Lambeta et al., 2020). The reviewed articles consistently emphasized that data representation is pivotal: tactile signals are often encoded as images or spatio-temporal matrices, allowing the application of deep learning architectures originally designed for visual data (Zhang & Sun, 2021). This conceptual shift—from raw analog signals to image-based tactile embeddings—has substantially improved model generalization and interpretability. The findings also revealed an emerging trend toward hybrid tactile datasets that integrate real-world measurements with synthetic data generated via physics-based simulation (Guo et al., 2022). This hybridization mitigates the limitations of costly and time-consuming physical experiments while supporting domain randomization for learning-based transfer. Similar conclusions were drawn in prior work by Yuan et al. (2017), which demonstrated that combining synthetic tactile data with experimental samples enhances a model's capacity to adapt to unseen surfaces and dynamic friction patterns. Furthermore, the establishment of benchmarking tasks—such as slip detection, grasp stability prediction, and material classification—has fostered objective performance comparisons across studies (Calandra et al., 2018). The field thus appears to be coalescing around shared standards and open repositories, enabling the reproducibility and cross-validation necessary for the maturation of tactile machine learning.

The third major finding involves the sim-to-real transfer of tactile sensing and control models, which represents one of the most significant challenges in deploying tactile systems in real-world manipulation scenarios. The results show that while simulations offer a safe and scalable environment for generating large datasets, the performance of models trained solely in simulation often degrades when exposed to the stochasticity and material variability of the physical world (Kumar et al., 2021). Theoretical and empirical studies reviewed here identified three dominant strategies for mitigating the simulation–reality gap: domain randomization, adversarial feature alignment, and hybrid fine-tuning (Fang et al., 2023). Domain randomization introduces stochastic variability in simulated tactile environments to encourage generalization across different object properties and lighting conditions. Adversarial learning leverages discriminators to minimize the discrepancy between simulated and real tactile features, producing invariant representations transferable across domains (Zhang et al., 2022). Hybrid fine-tuning further adapts pretrained simulation models to real tactile data using limited real-world samples, balancing data efficiency with empirical accuracy (Sferrazza & Dandrea, 2019). This layered transfer methodology aligns with findings from vision-based robotics, where domain adaptation has similarly improved the sim-to-real robustness of perceptual models (Calandra et al., 2018). However, unlike visual data, tactile signals are influenced by non-idealities such as hysteresis, sensor drift, and contact deformation, necessitating domain-specific adaptation pipelines. The reviewed literature suggests that combining tactile with visual modalities during sim-to-real transfer yields superior performance, as multimodal cues compensate for modality-specific weaknesses (Lambeta et al., 2020). These findings underscore that tactile sim-to-real transfer is not merely a technical challenge but a conceptual bridge connecting sensor physics, data modeling, and adaptive control.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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