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Review on Dexterous Hand Technology Empowered by Computer Science: Multidimensional Integration and Innovative Progress

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Abstract. Dexterous hand technologies have emerged as a critical frontier in robotics, driven by growing demands for human-like manipulation in complex and dynamic environments. This review explores how advancements in computer science—particularly in intelligent control, sensor fusion, and machine learning—have transformed the design and deployment of dexterous robotic hands. We analyze three major integration pathways: data-driven control algorithms that improve real-time adaptability, application-specific solutions in domains such as healthcare and manufacturing, and multimodal perception frameworks that enhance manipulation precision through the fusion of tactile, visual, and proprioceptive data. The review also identifies key challenges, including perception latency, data scarcity, limited generalization, and deployment barriers. Finally, we propose future research directions involving context-aware learning, simulation-based training, lightweight architectures, and interdisciplinary collaboration. The findings underline the importance of computational intelligence in enabling robotic hands to achieve robust, safe, and flexible performance in real-world settings.

Keywords: Dexterous Hand; Computer Science; context-aware learning simulation-based training; Multidimensional Integration.

1. Introduction

Dexterous hands have long been regarded as one of the most challenging and promising research areas in robotics and intelligent systems. With the rapid development of applications such as service robots, industrial automation, prosthetics, and teleoperation, the demand for highly adaptive, precise, and human-like manipulation capabilities has continued to grow[1]. Traditional mechanical designs and control methods, while achieving considerable progress, often face limitations in flexibility, perception, and autonomy when dealing with complex and dynamic environments[2].

Fig 1. Typical dexterous hand.

Recent advancements in computer science have provided new impetus for the evolution of dexterous hand technologies. Machine learning algorithms, multimodal sensor fusion, real-time decision-making systems, and virtual simulation environments have collectively reshaped the landscape of dexterous manipulation. By leveraging these computational tools, researchers can enhance the perception, control, and adaptability of robotic hands beyond what conventional engineering approaches allow.[3]

The integration of computer science into dexterous hand research has enabled several key breakthroughs. Machine learning techniques allow systems to learn optimal grasping and manipulation strategies directly from data[4], reducing the reliance on manually engineered control rules. Vision-based and multimodal perception systems, powered by deep learning, provide richer environmental awareness[5], enabling more intelligent interaction with uncertain surroundings. Reinforcement learning offers a framework for dexterous hands to autonomously acquire skills through trial and error, while digital twins and simulation environments accelerate development cycles by offering safe and efficient training grounds.[6]

Moreover, computer-enabled dexterous hands are now being deployed across various domains. In healthcare, robotic hands equipped with tactile sensors assist in delicate surgical operations.[7] In manufacturing, intelligent grippers are replacing human labor for precision assembly tasks. In assistive technologies, prosthetic hands embedded with real-time feedback systems offer amputees improved motor functions and autonomy. These achievements demonstrate the broad impact of computer science on real-world manipulation tasks.[8]

Despite these achievements, many challenges remain. Issues such as perception latency, limited generalization across tasks, high data dependency, and difficulties in real-world deployment still hinder the practical realization of truly autonomous and adaptable robotic systems.[9] These limitations highlight the urgent need for cross-disciplinary research integrating mechanical design, control theory, and computational intelligence[10].

This review aims to systematically summarize recent advances in dexterous hand technologies empowered by computer science, with a particular emphasis on multidimensional integration of computational methods.

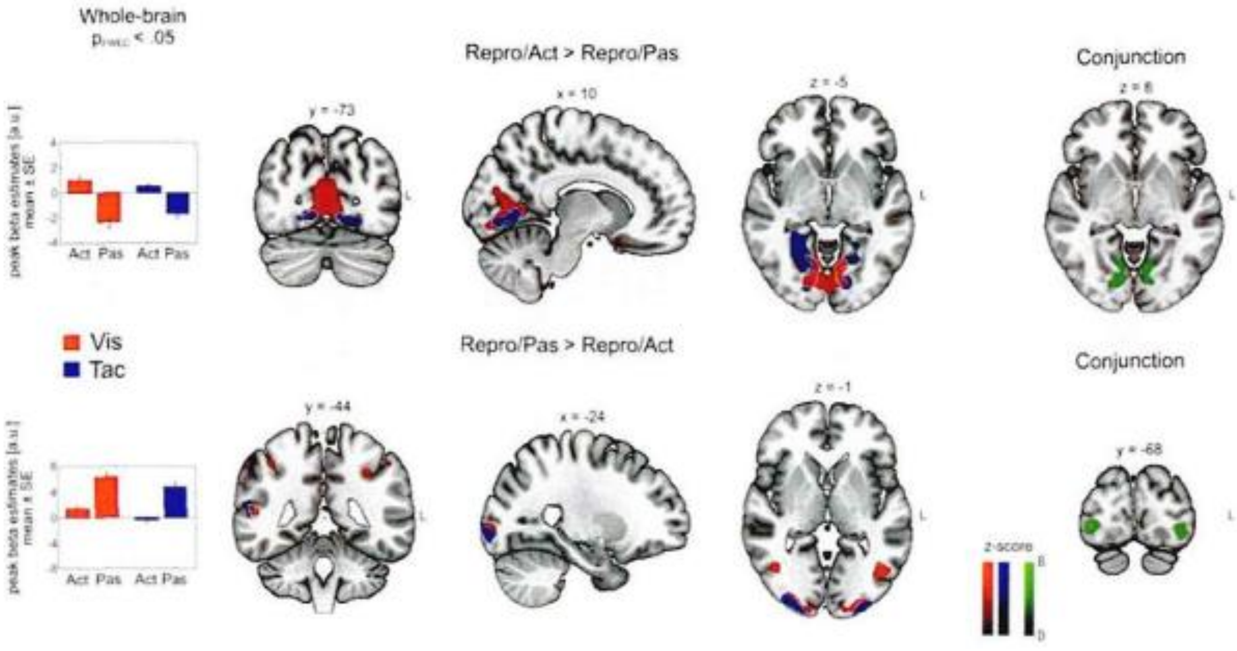


Fig 2. The reflection of hand movement visual touch coordination in the brain nerves.

2. Multidimensional Integration of Computational Methods

2.1. Intelligent Control Algorithms for Dexterous Hands

The development of intelligent control algorithms plays a pivotal role in enhancing the adaptability and autonomy of dexterous robotic hands. Unlike traditional rule-based control approaches that rely heavily on explicit physical modeling[11], contemporary methods driven by computational intelligence enable systems to dynamically learn from experience[12], optimize control strategies, and respond flexibly to complex, time-varying environments.

Fig 3. Five finger hand differentiable force closure estimation.

One of the foundational frameworks in this domain is the Kalman filter (KF)[13], which has been widely used to estimate internal battery states due to its excellent noise-handling capability and real-time performance. Sarmah (2019) emphasized that such filters, when adapted to robotic control, enable stable and recursive estimation of hidden state variables[14], making them particularly effective in tracking hand joint positions and predicting tactile responses under sensor noise. However, classical KF is limited by its assumption of linearity, which rarely holds true in high-DoF (degrees of freedom) robotic hands operating in unstructured environments.[15]

To address the challenges posed by nonlinearity, researchers have advanced the extended Kalman filter (EKF) and unscented Kalman filter (UKF[16]). Hasib (2021) argued that UKF provides a more accurate approximation of nonlinear transformations without requiring Jacobian matrices, thus reducing model dependency and improving convergence in dynamic tasks such as object manipulation with varying stiffness and shape[17]. This adaptability is critical for real-world deployments where prior knowledge of object properties may be limited or unreliable.

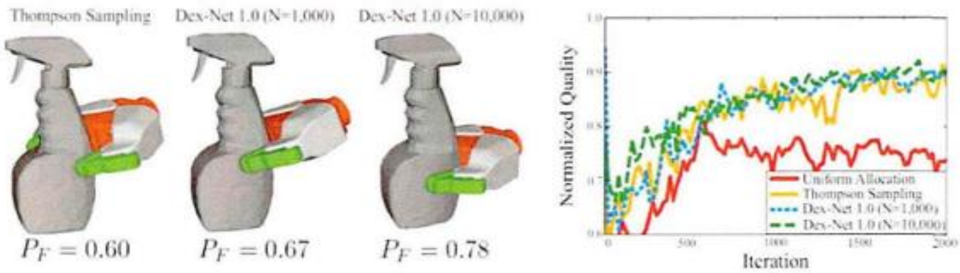


Fig 4. 3D grasping model and grasping quality evaluation.

Beyond filter-based strategies, the particle filter (PF[18]) has emerged as a powerful tool for stochastic control in dexterous manipulation. Elmahallawy (2022) noted that PF-based methods are particularly effective in handling multi-modal distributions and model uncertainties, enabling robust control even when the sensor data are sparse or partially missing[19]. Such algorithms allow robotic hands to maintain functional grasping even under disturbances, a significant advantage in tasks requiring force compliance or when dealing with deformable materials.

Furthermore, the integration of adaptive filtering with control feedback loops has shown promise[20]. Su (2022) introduced the adaptive extended Kalman filter (AEKF), which dynamically tunes its noise covariance parameters using feedback from observed states. Applied to dexterous hands, this means the system can adjust its confidence in sensor inputs and internal predictions based on real-time performance, allowing for more resilient control under unpredictable interactions.

Collectively, these intelligent control algorithms—ranging from advanced Kalman-based filters to probabilistic sampling methods—demonstrate how computational methods rooted in estimation theory can significantly enhance the autonomy and precision of dexterous hands. Their ability to generalize across varying conditions and self-adjust to uncertainties marks a substantial step toward robotic hands that can perform in diverse and dynamic real-world scenarios.

2.2. Applications of Dexterous Hands in Key Domains

The practical deployment of dexterous hands has witnessed notable success across several critical domains, including healthcare, manufacturing, and assistive technologies. These applications are not only technologically demanding but also benefit significantly from advances in computational modeling and intelligent estimation frameworks originally developed in the field of energy systems and adapted for robotic manipulation[21].

In the medical field, dexterous robotic hands have been used to perform minimally invasive surgeries with enhanced precision and reduced human fatigue. Wang (2022) emphasized the importance of accurate state estimation in highly dynamic and safety-critical scenarios[22]. Drawing parallels from lithium-ion battery systems, the use of layered estimation techniques in surgical robotics ensures stability and responsiveness during real-time tasks such as tissue manipulation, where precision is vital.

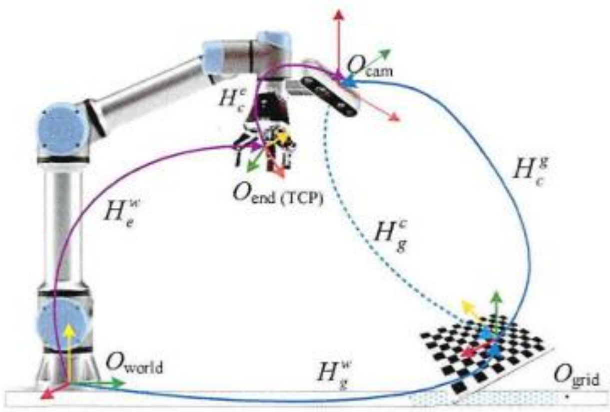


Fig 5. Robot Hand Eye Calibration System Model.

The manufacturing sector similarly benefits from intelligent dexterity, particularly in precision assembly and adaptive grasping. He (2020) proposed a staged estimation algorithm to dynamically adjust control parameters based on shifting internal states. When applied to robotic grippers, this concept translates into multistage manipulation strategies[23], where grip strength, orientation, and contact force can be adaptively refined in real-time as components vary in size, shape, or material stiffness.

In assistive technology, prosthetic hands have made tremendous progress by incorporating adaptive sensory and control algorithms. Wu (2022) highlighted the relevance of electrochemically modeled estimation systems in predicting non-observable internal parameters, which parallels the challenge of inferring user intent and muscle signals in prosthetics[24]. By embedding models that anticipate and adjust for user variability, modern prosthetic hands provide users with more fluid, natural, and autonomous interaction.

Moreover, in human-robot interaction contexts, especially in rehabilitation or social assistance, trust and responsiveness are paramount[25]. Wu (2021) introduced an approach based on correlation entropy extended Kalman filtering that enhances robustness in noisy environments. This principle supports the development of dexterous hands that can operate under uncertain sensor input conditions, such as erratic electromyographic signals from residual limbs or inconsistent tactile feedback in shared control scenarios[26].

Overall, these applications demonstrate the broad adaptability of intelligent estimation concepts across diverse domains. By transferring estimation techniques from battery diagnostics to real-time robotic control, researchers have enabled dexterous hands to function in increasingly complex environments while maintaining reliability, adaptability, and user-centered responsiveness.

2.3. Multimodal Sensor Fusion in Dexterous Hands

Multimodal sensor fusion is a cornerstone of next-generation dexterous hand systems, enabling richer environmental awareness, better manipulation precision, and improved robustness against uncertainty. By integrating information from diverse sensors—such as tactile arrays, vision systems, force-torque sensors, and electromyographic (EMG) signals—robotic hands can achieve human-like responsiveness in complex, unstructured environments[27].

One effective approach to sensor fusion is the combination of neural networks and probabilistic estimators. Li (2020) introduced a hybrid method that combines gated recurrent neural units with a Huber-M estimation-based Kalman filter to estimate the state of lithium-ion batteries. This architecture, originally used to handle non-Gaussian noise in battery systems, offers a valuable analogy for robotic hands integrating noisy tactile and visual inputs[28]. Such fusion frameworks allow the hand to maintain stable grasping behavior even when confronted with fluctuating sensory data, a common scenario in real-world object manipulation.

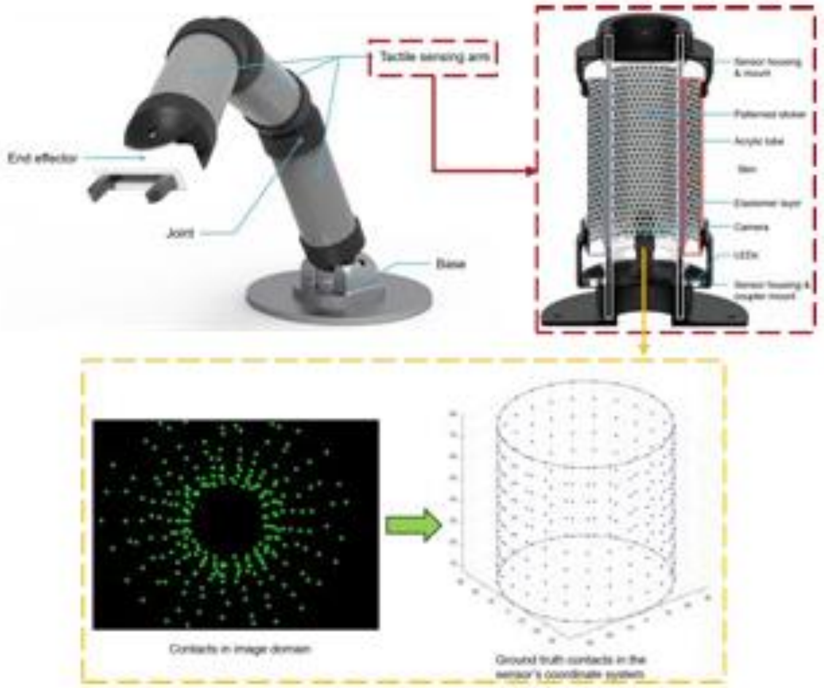


Fig 6. VTacArm Sensor System.

Complementary to neural approaches, algorithm-level fusion strategies have also been developed. Wang (2021) summarized multiple fusing algorithm schemes for battery SOC estimation[29], emphasizing modular integration of heterogeneous signals. Transferred to robotic perception, this principle enables dexterous hands to combine high-frequency tactile data with low-frequency visual cues, balancing responsiveness and context awareness. In tasks such as tool use or in-hand object manipulation, this fusion is essential to dynamically reconfigure grip or apply nuanced force control based on feedback latency and confidence levels.

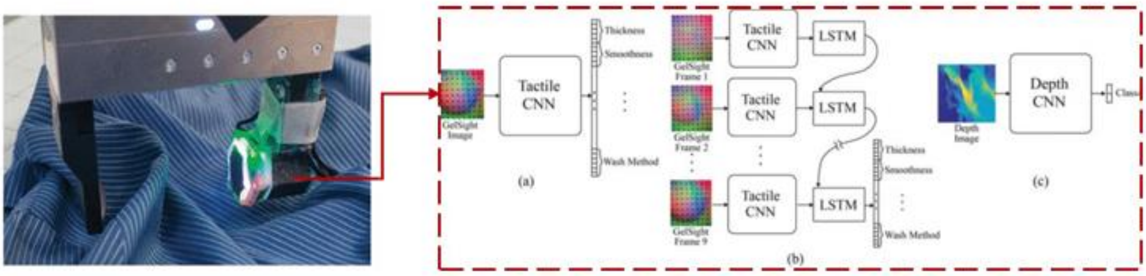


Fig 7. Clothing attribute perception method.

Furthermore, multimodal fusion is critical when working with feedback from uncertain or partially observable sources. Li (2010) compared a range of ampere-hour integration methods in state estimation and emphasized the importance of dynamically correcting cumulative drift. In robotic systems, an analogous challenge occurs when combining proprioceptive signals (e.g., joint positions[30]) with externally sensed information. Here, sensor fusion not only boosts precision but also mitigates the degradation of accuracy over time.

In practical implementations, the robustness of fusion models to changes in system parameters is key. Luo (2020) introduced a capacity correction-based integration approach to enhance SOC[31] estimation stability under variable conditions. Applied to dexterous hand systems, similar logic can be adopted to account for sensor degradation or adaptive recalibration—especially important for wearable prosthetics or mobile manipulators operating under shifting thermal or electrical loads.

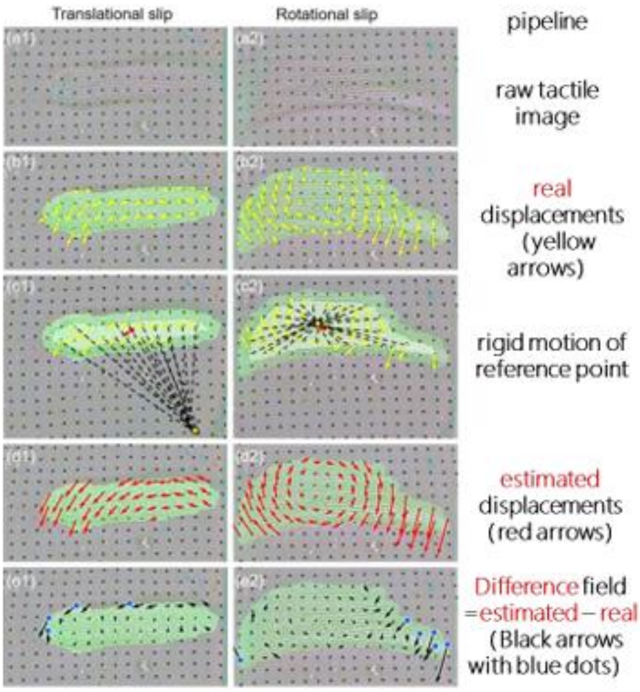


Fig 8. The slip detection algorithm proposed by Luo et al.

Taken together, these fusion methods demonstrate that cross-domain estimation strategies, when adapted thoughtfully, can substantially improve the effectiveness and resilience of sensor-rich robotic hands. As the fidelity and diversity of sensors continue to evolve, the need for robust fusion algorithms remains central to achieving reliable and intelligent manipulation.

3. Challenges and Future Directions

3.1. Perception and Latency Issues

Perception latency remains one of the most pressing challenges in deploying dexterous hands in dynamic and unstructured environments. The ability of a robotic hand to interpret multimodal sensory input and generate timely control responses is central to safe and effective manipulation[32]. However, sensor processing delays, limited computational throughput, and asynchronous signal fusion often result in sluggish response times or misinterpretation of environmental feedback.

Edge et al. (2021) emphasized that real-time estimation systems, particularly in energy management scenarios, suffer significantly when perception and control are decoupled temporally. This insight translates directly to robotics[33], where delayed sensor fusion may cause unstable grasps or failure in task execution. The problem becomes more critical when tactile and visual data must be combined, especially in tasks involving deformable or slippery objects. Xie et al. (2018) proposed an improved filtering algorithm that compensates for perception noise and delay in nonlinear systems. Their method, initially designed for battery health monitoring, serves as a viable analogy for latency compensation in robotic control loops. In dexterous hands, similar filters can be implemented to predict contact states milliseconds ahead, effectively smoothing out jittery sensor readings and enabling continuous contact feedback. Additionally, Zhang et al. (2018) pointed out that system response time is not only affected by sensor delay but also by computational model complexity. As dexterous hands integrate more advanced perception modules[34], such as deep learning-based vision and probabilistic tactile interpretation, the trade-off between computational demand and latency tolerance becomes sharper. Efficient model design and hardware-software co-optimization are therefore essential. Huang et al. (2019) further argued that robustness to perception error must be integrated at the algorithmic level. In their work on state estimation frameworks, they introduced adaptive noise modeling to handle fluctuating sensory reliability. Applying this to robotic hands enables graceful degradation[35], where the system can maintain partial functionality under degraded perception, thus improving safety and reliability in human-robot interaction. Together, these insights underscore that overcoming latency in perception is not merely a hardware issue but requires holistic algorithmic design, predictive estimation, and adaptive fusion—all of which are critical for enabling fast, safe, and intelligent dexterous manipulation.

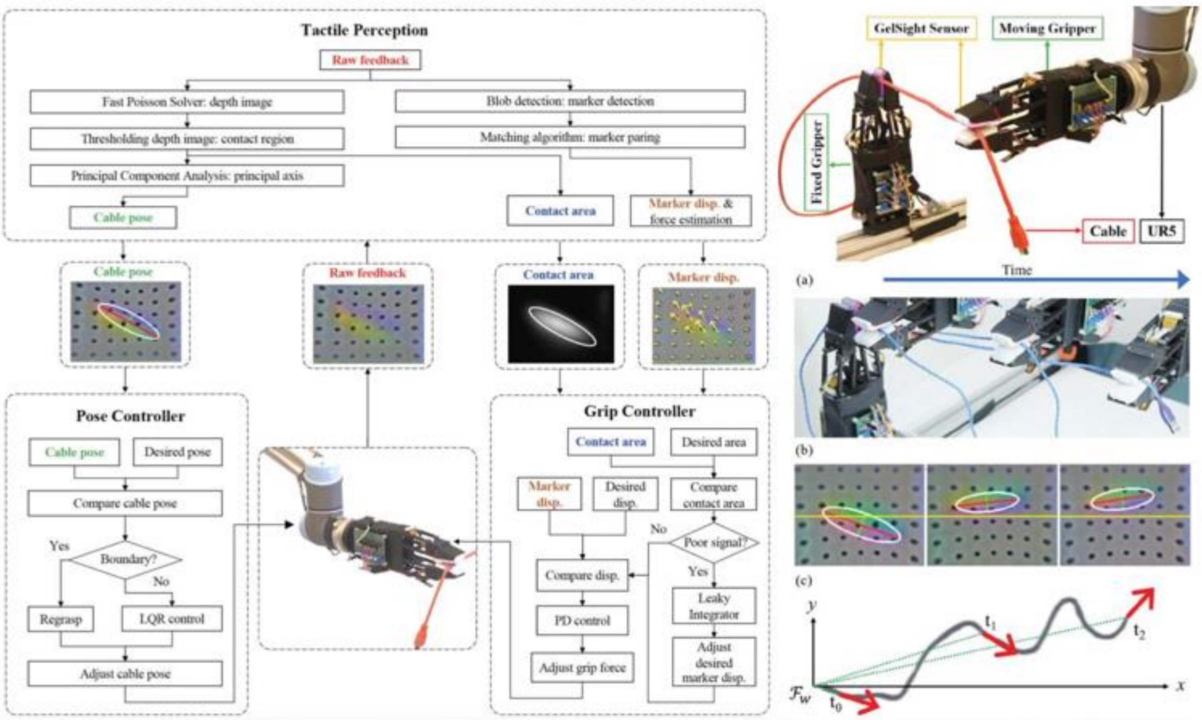
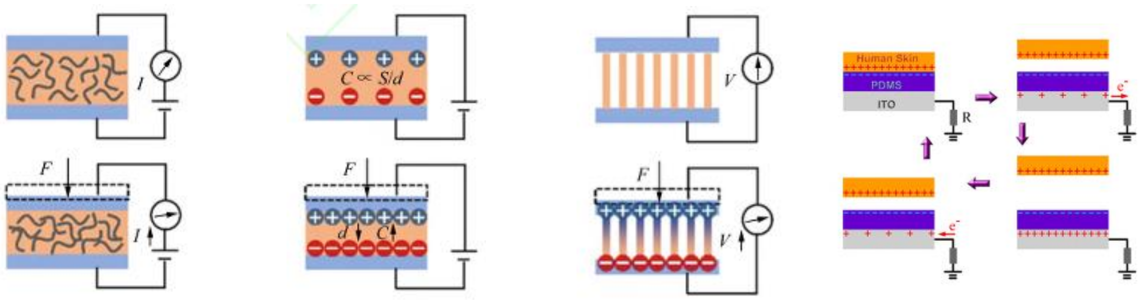


Fig 9. Flexible manipulation of deformable linear objects based on tactile information.

3.2. Data Bottlenecks and Generalization Gaps

The development of intelligent dexterous hand systems depends heavily on large volumes of high-quality training data. Yet, the collection, labeling, and management of such data across diverse manipulation tasks and environmental conditions remain significant bottlenecks. This limitation hampers both the scalability of machine learning-based methods and the generalization of control policies across domains.

Ming et al. (2021) highlighted that traditional state estimation systems often fail to generalize beyond their design conditions due to rigid parameter configurations and insufficient data diversity. This challenge is mirrored in robotic hands trained with task-specific datasets that may not capture the variability encountered in real-world manipulation. As a result, control models often overfit to laboratory scenarios and struggle with unfamiliar objects or lighting conditions[36]. Li et al. (2020) proposed a fusion algorithm that integrates gated recurrent units with robust Kalman filters, achieving greater adaptability in noisy environments. Although originally used for battery SOC prediction, this fusion strategy informs the design of generalizable robotic systems that can interpolate sensor data from incomplete or variable sources. Such adaptability is crucial for manipulation tasks in cluttered or partially observable scenes. Wang et al. (2021) further emphasized that fusion methods relying on fixed model parameters are vulnerable to performance degradation when encountering unseen input patterns. This suggests that dexterous hands must not only fuse data but also dynamically adjust their internal representations through meta-learning or domain adaptation techniques[37]. Zheng et al. (2018) addressed the issue of data bottlenecks from a model compression perspective, advocating for lightweight architectures that maintain performance with reduced training data. In robotic applications, this is particularly relevant for embedded systems where storage and processing constraints prevent deployment of large models. Their insights suggest that smaller, well-tuned models may yield better generalization in practical manipulation tasks than oversized, data-hungry counterparts. Collectively, these studies underscore the urgent need to improve data efficiency and generalization capacity in dexterous hand systems[38], through smarter model design, flexible fusion algorithms, and scalable data augmentation strategies.



(Piezoresistive type). (Capacitive type). (Piezoelectric type). (Frictional electric type).

Fig 10. Illustration of different sensing mechanisms.

3.3. Real-World Deployment Constraints

Translating laboratory-level dexterous hand systems into real-world deployment remains a formidable challenge. While many prototypes exhibit promising capabilities under controlled conditions, performance often deteriorates when faced with the unpredictable dynamics, physical wear, environmental variability, and system integration issues encountered in real operational contexts[39].

Dang et al. (2017) noted that many intelligent estimation systems fail in long-term use due to lack of robustness to sensor drift, component aging, and ambient interference. These factors are particularly acute in robotic hands, where tactile and proprioceptive sensors are continuously exposed to mechanical stress, variable temperatures, and noise from surrounding equipment. Ensuring stable operation over extended periods therefore requires fault-tolerant design and online recalibration mechanisms. Schmidt et al. (2010) explored the tension between computational complexity and real-time feasibility in embedded control systems[40]. Their study suggests that control algorithms with high theoretical performance may not be viable on power-limited platforms, such as mobile or wearable robotic hands. This reflects a common deployment constraint: even when algorithms perform well in simulation, they often cannot meet latency, energy, or memory constraints in practice. Available literature (2020) further indicates that software-hardware integration issues—especially when deploying systems that rely on deep learning or sensor fusion—can cause instability or delays in real-time feedback loops[41]. Robotic hands must not only respond quickly, but do so reliably under strict constraints; this demands lightweight implementations, asynchronous communication handling, and cross-layer debugging between sensors, middleware, and motion control units. He et al. (2011) emphasized the need for domain-specific adaptation of estimation models in practical deployments. Their analysis revealed that models optimized for general conditions may exhibit poor accuracy in real environments unless explicitly retrained or adapted. For robotic hands, this suggests the necessity of adaptive learning modules that tune control responses based on live feedback, wear patterns, and task histories[42]. Altogether, these insights make clear that successful deployment of dexterous hands requires more than algorithmic accuracy—it demands resilient system engineering, computational efficiency, environmental robustness, and continuous adaptation to real-world variability.

3.4. Future Research Directions

As the field of dexterous manipulation continues to evolve, future research must address the current limitations by pursuing more holistic, adaptive, and resource-efficient strategies[43]. These directions span across algorithmic innovation, system-level integration, and human-centered design, aiming to make robotic hands more intelligent, robust, and deployable.

Jiao et al. (2020) argued that future state estimation models must transition from static parameterization to context-aware adaptability. In robotic hands, this suggests implementing meta-learning architectures or self-supervised mechanisms that evolve with user intent, environmental changes, and task progression. Such adaptability will be crucial for developing prosthetic or wearable systems that remain effective over long-term, real-life use. Moura et al. (2017) proposed a multi-layer data-driven framework for health prediction, emphasizing hierarchical learning across heterogeneous sources[44]. This layered perception strategy can be directly applied to dexterous hands, allowing them to reason not only about object properties but also about their own functional states—detecting internal wear, grip inconsistencies, or latency buildup in real time. Zhu et al. (2017) emphasized the importance of simulation-based pretraining in reducing real-world data dependency. Digital twins and physics-informed[45] simulation tools offer safe and efficient grounds for policy learning and refinement. When paired with real-world fine-tuning, this hybrid approach can accelerate deployment while minimizing hardware fatigue and data collection costs. In addition to these algorithmic directions, future systems should also prioritize explainability and safety[46]. As robotic hands are increasingly embedded in human-centered environments—be it homes, clinics, or factories—transparent decision-making processes and safety constraints must be tightly integrated at both hardware and software levels. To that end, collaboration across disciplines—robotics, machine learning, control theory, biomechanics[47], and cognitive science—will be essential to create truly intelligent, context-sensitive, and trustworthy dexterous hands that can operate alongside humans in meaningful and impactful ways.

4. Conclusion

This review systematically investigates the pivotal role of computer science in advancing dexterous hand technologies, focusing on the multidimensional integration of computational methods. Key contributions and conclusions are as follows:

1. Multidimensional Integration of Computational Methods

Intelligent Control Algorithms: Advanced algorithms such as Kalman filters (KF, EKF, UKF), particle filters (PF), and adaptive estimation methods (e.g., AEKF) enhance the real-time adaptability and robustness of dexterous hands. These techniques enable dynamic learning from data, optimize control strategies, and address nonlinearity and uncertainty in complex environments.

Domain-Specific Applications: In healthcare, manufacturing, and assistive technologies, dexterous hands empowered by computational models (e.g., state estimation and battery modeling strategies) achieve improved precision in surgical operations, adaptive grasping in assembly tasks, and natural feedback in prosthetics.

Multimodal Sensor Fusion: By integrating tactile, visual, and proprioceptive data through neural networks, probabilistic estimators, and hybrid fusion frameworks, robotic hands achieve human-like perception, enhancing manipulation precision and resilience to noisy or incomplete sensory inputs.

2. Key Challenges

Perception Latency: Delays in sensor processing and computational bottlenecks hinder real-time responsiveness, particularly in dynamic scenarios involving deformable objects.

Data Bottlenecks: Limited high-quality training data and poor generalization of machine learning models across diverse tasks restrict the scalability of intelligent dexterous systems.

Real-World Deployment: Issues such as sensor drift, hardware wear, computational complexity, and system integration challenges limit the transition from laboratory prototypes to practical applications.

3. Future Directions

Context-Aware Learning: Develop meta-learning and self-supervised architectures to enable adaptive control based on user intent and environmental changes.

Simulation-Based Training: Leverage digital twins and physics-informed simulations to reduce data dependency and accelerate algorithm development.

Lightweight Architectures: Design efficient, low-power models to address hardware constraints in embedded systems (e.g., mobile or wearable robotic hands).

Interdisciplinary Collaboration: Integrate robotics, machine learning, biomechanics, and cognitive science to create trustworthy, human-centered dexterous systems.

The integration of computer science—particularly through data-driven control, sensor fusion, and adaptive algorithms—has transformed dexterous hands from rigid, pre-programmed devices into intelligent, context-aware manipulators. While challenges like latency, data scarcity, and deployment barriers persist, the reviewed advancements and proposed future directions highlight a clear path toward robotic hands that can operate safely, flexibly, and autonomously in real-world environments, with broad implications for industry, healthcare, and daily life.

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