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Review

Anthropomorphic Soft Hand: Dexterity, Sensing, and Machine Learning

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Abstract: Humans possess dexterous hands that surpass those of other animals, enabling them to perform intricate, complex movements. Soft hands, known for their inherent flexibility, aim to replicate the functionality of human hands. This article provides an overview of the development processes and key directions in soft hand evolution. Starting from basic multi-finger grippers, these hands have made significant advancements in the field of robotics. By mimicking the shape, structure, and functionality of human hands, soft hands can partially replicate human-like movements, offering adaptability and operability during grasping tasks. In addition to mimicking human hand structure, advancements in flexible sensor technology enable soft hands to exhibit touch and perceptual capabilities similar to humans, enhancing their performance in complex tasks. Furthermore, integrating machine learning techniques has significantly promoted the advancement of soft hands, making it possible for them to intelligently adapt to a variety of environments and tasks. It is anticipated that these soft hands, designed to mimic human dexterity, will become a focal point in robotic hand development. They hold significant application potential for industrial flexible gripping solutions, medical rehabilitation, household services, and other domains, offering broad market prospects.

Keywords: anthropomorphic soft hand; soft robotics; tactile sensor; dexterous

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1. Introduction

Over millions of years of evolutionary development, humans have developed remarkably dexterous hands that are unmatched by those of other animals. The complex structure of the human hand, encompassing an assemblage of bones, ligaments, and muscles, collaborates synergistically to combine robustness and delicate control, enabling both forceful and intricate maneuvers. In robotics, the advent of robots seeks to either replace or assist human efforts in executing specific tasks and operations. Robotic hands and end effectors are crucial components of robotic systems that directly interact with the external environment and are responsible for executing various actions, grasping, and manipulation tasks.

To enhance the flexibility of mechanical hands, traditional rigid robotic hands incorporate numerous motors, linkages, gears, and springs to achieve the desired functionality. However, this approach significantly increases the complexity of the structure. Although rigid humanoid hands are precise and responsive, they can cause irreparable damage when handling fragile objects [1–3]. Additionally, the potential weight of rigid structures can pose an injury risk during human–robot interactions. Contrarily, anthropomorphic soft hands leverage the inherent flexibility of their materials, offering remarkable advantages, such as compliance and high resistance to external impact, compression, torsion, and collisions [4–6]. These benefits stemming from their "soft" characteristics have prompted increased research in related studies.

Soft hands have received more attention due to their innate compliance, permitting interaction with the environment via techniques akin to those of natural organisms. The inherent compliance reduces the stringent requirements for complex and precise kinematic modeling and high-resolution sensor feedback, simplifying traditional grasping problems encountered by rigid robotic hands. The grasp of soft hands can be effectively controlled by adjusting the input pressure. The passive adaptability and compliance in their structure significantly simplify grasp planning problems [7,8]. Therefore, soft hands are a promising choice for human-centered machine grasping tasks, offering performance benefits such as interaction safety, grasp reliability, and cost-efficacy.

The recreation of humanoid dexterous hands is an ongoing pursuit in the field of robotics. By imitating the shape, structure, and functionality of human hands, soft humanoid dexterous hands can partially achieve human-like movements, providing broad adaptability and operability in grasping and hand manipulation [9,10]. It is foreseeable that soft humanoid dexterous hands will become a focal point in the development of robotic hands, finding increasingly widespread applications and market prospects in areas such as flexible grasping solutions in industrial production [11,12], medical rehabilitation [13–16], and home services [17,18].

However, there are several differences between human and soft hands. First, soft hands are still unable to match the flexibility and adaptability of human hands. Human hands possess exceptional perception and adjustment abilities, adapting to various shapes and environments, while soft hands face challenges when dealing with objects in complex three-dimensional (3D) spaces [19,20]. Second, the control systems of soft hands are relatively complex, potentially requiring advanced algorithms and sensing technologies to achieve fine manipulation similar to human hands [21,22]. The high coordination and flexibility exhibited by human hands during various tasks may necessitate further research and technological innovation for soft hands, while durability and stability present additional challenges [23,24], requiring attention.

This review aims to provide an overview of the main directions in soft hand development, address the challenges and current issues in the research of soft humanoid dexterous hands, and explore potential future trends. The crucial factors that determine whether a soft hand can match the capabilities of a human hand are its gripping/manipulation performance and perception capability. Therefore, this review primarily focuses on the evolution of gripping/manipulation performance and advancements in tactile perception of soft hands. Additionally, the inclusion of machine learning in soft robots is discussed, as it enables them to possess more sophisticated perception abilities and improved gripping/manipulation strategies, allowing them to intelligently adapt to various environments and tasks. Since the materials, manufacturing processes, and driving methods for soft hands have been widely investigated [25–29], these aspects are not extensively discussed in this review. Popular materials, manufacturing methodologies, driving force, and control policy used in soft hands are listed in Table 1.

Table 1. Summary of anthropomorphic soft hands.

Materials	Fabrication	Actuation	Control	DOF	Main Features	Category	Year	Ref
Dragon skin-10, Dragon skin-20, Dragon skin-30, Ecoflex 00-10	Casting molding	Pneumatic	Closed-loop control	14	Flexible thenar	Anthropomorphic dextureous hand	2022	[4]
Dragonskin 10, Ecoflex 00-30	Casting molding	Pneumatic	coordinated control	6	Replicate the human-like grasp postures	Anthropomorphic dextureous hand	2022	[7]
Silicone rubber, fibers	Casting molding	Pneumatic	Open-loop control	12	Flexible palm	Underactuated anthropomorphic hand	2013	[8]
Dragon skin 30	Casting molding		Open-loop control	21		Soft parallel palm	2023	[19]
Ecoflex 00-50, Mold Star 30, ABS	Casting molding	Pneumatic	Open-loop control	13	Grasping planning	Anthropomorphic dextureous hand	2018	[20]
Dragon Skin 10, fibers	Casting molding	Pneumatic	Open-loop control	22	Flexible operation function	Anthropomorphic dextureous hand	2022	[30]
TPU, ABS	—	Fluidic and Tendon actuation	Open-loop control	5	SMA-Based Exo-Glove	Soft Exo-Glove	2023	[31]
Resin, PET, Nylon gauze	Planar laser cutting and stacking	Pneumatic	Open-loop control	6	Hybrid pneumatic actuators	Underactuated anthropomorphic hand	2021	[32]
VytaFlex 20, ELASTOSIL M 4601	3D printing, soft lithography	Pneumatic	Open-loop control	12	Multi material 3D printed	Anthropomorphic dextureous hand	2020	[33]
Dragon skin-10, Dragon skin-30, fibers	Casting molding	Pneumatic	Open-loop control	3	SMP actuated	Dextureous finger	2016	[34]
Dragon Skin 10, Ecoflex 00-30, nylon thread, fibers	Casting molding	Pneumatic	Open-loop control	12	Highly integrated design	Anthropomorphic dextureous hand	2023	[35]
Vero, Agilus30	3D printing	Pneumatic	Closed-loop control	5	3D printed fingers	Underactuated anthropomorphic hand	2021	[36]
PDMS, CNTs	3D printing	Light-driven	Open-loop control	5	SMA actuated	Underactuated anthropomorphic hand	2020	[37]
PDMS, SMA, fiberglass	Casting molding	Tendon-driven	Open-loop control	10	SMA actuated	Underactuated anthropomorphic hand	2023	[38]
TPU, SMA	3D printing	SMA	Open-loop control	10	Elastic joints and soft pads	Anthropomorphic dextureous hand	2014	[39]
TPU	3D printing	Pneumatic	Open-loop control	10	Soft-Rigid Hybrid fingers	Anthropomorphic dextureous hand	2023	[40]
Silicone rubber, ABS	—	Pneumatic	Open-loop control	5	Self-healing soft fingers	Underactuated anthropomorphic hand	2017	[41]
Dragonskin-10, ecoflex 00-30, fibers	Casting molding	Pneumatic	Closed-loop control	-	Deployable, atraumatic grasper	Surgical grasper	2014	[42]
Smooth-Sil 936, fibers	Casting molding	Fluid-driven	Open-loop control	1	Pneu-net actuator	Dextureous finger	2014	[43]
Ecoflex-30, SMA, PDMS	Casting molding	SMA	Closed-loop control	5	ECF jet	Underactuated anthropomorphic hand	2011	[44]
TPU	3D printing	Tendon	Open-loop control	5	Completely soft	Soft Exo-Glove	2021	[45]
Electro-conjugate fluid(ECF)	—	ECF jet	Open-loop control	5	Planar Laser Cutting and Stacking	Underactuated anthropomorphic hand	2021	[46]
NinjaFlex, particles	3D printing	Pneumatic	Closed-loop control	3	Humanoid hand skeleton	Dextureous finger	2019	[47]
Agilus30, Vero	3D printing	Pneumatic	Open-loop control	5	Pneumatic Exo-Glove	Soft Exo-Glove	2016	[48]
Dragon Skin 10, Ecoflex 00-30	—	Pneumatic	Myoelectric control	4	3D printed	Underactuated anthropomorphic hand	2017	[49]
Dragon skin 30, paper	Casting molding	Pneumatic	Open-loop control	4	Dualmodule pneumatic actuator	Nonanthropomorphic Grippers	2020	[50]
Silicone, PLA	Casting molding	Tendon-driven	Open-loop control	2	Two-finger grip	Nonanthropomorphic Grippers	2022	[51]
Silicone, fiber	Casting molding	Pneumatic	Open-loop control	7	Active Palm	Underactuated anthropomorphic hand	2016	[52]
Vero White, Tango Black	3D printing		Open-loop control	18	Soft-rigid hybrid hand	Anthropomorphic dextureous hand	2018	[53]
TPU	3D printing	Pneumatic	Open-loop control	9	Hand sign language	Anthropomorphic dextureous hand	2019	[54]
Fiber, M4601, memory foam	Casting molding	hydraulic	Open-loop control	8	Underwater gripper	Nonanthropomorphic Grippers	2016	[55]
Tendons, Agilus Black material	3D printing	Tendon-driven	Open-loop control	3	Grasping	Underactuated anthropomorphic hand	2022	[56]
SmoothSil-960, MoldStar-30	Casting molding	Pneumatic	Open-loop control	9	Three-finger grip	Nonanthropomorphic Grippers	2023	[57]
Smooth-Sil 945, Ecoflex 00-30	Casting molding	Pneumatic	Open-loop control	8	Delicate In-hand manipulation	Soft robotic hand	2020	[58]

2. Dexterity and Gripping/Manipulation Performance

The grasping and manipulation capabilities of the human hand are highly complex and remarkable, showcasing the unique adaptability and flexibility developed throughout human evolution. First, the five fingers of the human hand possess independent motion capabilities, each with its own joint system that allows for individual flexion, extension, abduction, and adduction. This multi-joint structure grants the human hand exceptional dexterity, enabling the fingers to adapt to objects of various shapes and sizes (Figure 1a). The human hand also exhibits coordinated movements, allowing the fingers to work together to accomplish intricate manipulation tasks. The synergy of the fingers allows the human hand to perform precise grasping actions, such as delicately picking up small objects or adjusting the posture of larger objects. This coordination enables efficient object manipulation in various tasks. The flexibility of the human hand is driven by its highly complex biological structure and the remarkable neural control system, enabling independent, precise movements of the joints in a 3D space. The motion of these joints is intricately regulated by neural control systems, achieving highly coordinated and flexible control over the fingers. This section focuses on the dexterity and gripping/manipulation performance of different types of soft hands. The discussion categorizes these soft hands into three types based on their structure and functionality: non-anthropomorphic grippers, underactuated anthropomorphic hands, and anthropomorphic dexterous hands.

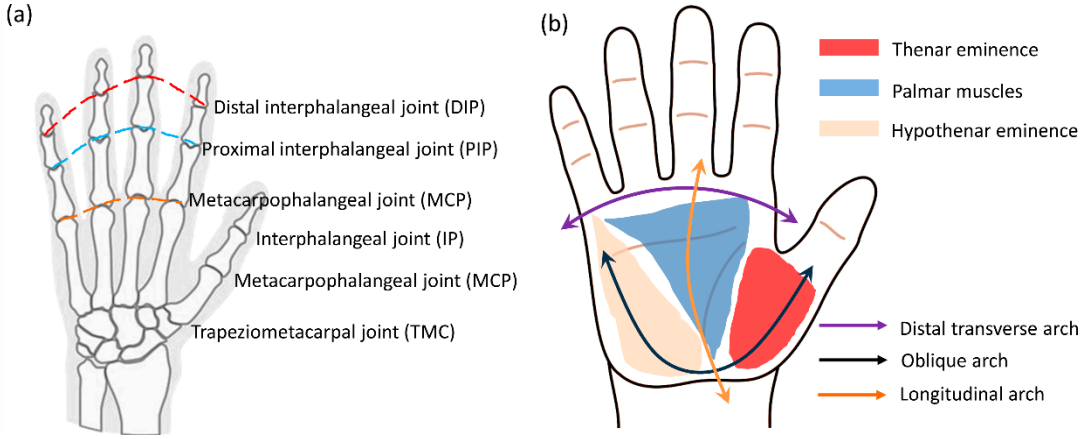


Figure 1. Schematic expression of (**a**) human hand joints; (**b**) and muscle groups and palm arches.

2.1. Nonanthropomorphic Grippers

As the end effector, the complete functionality of a robot hand is essential in the field of automation, with grasping being the most easily achievable operation. Therefore, two-finger and multi-finger soft grippers are fundamental for simulating human hand movements.

Soft grippers can grasp and release objects while executing specific actions. Pneumatic grippers are the most commonly employed, deforming when inflated, which enables approaching and securely grasping an object. The goal of research on robots using two-finger grippers for grasping tasks is to build a grasping recognition system that is fast, accurate, and appropriate for use by robotic hands [50,51]. However, multi-finger grippers are often employed since two-finger grippers frequently find it difficult to successfully complete grasping tasks when dealing with objects of complex shapes. Due to their multi-finger design, they are capable of multi-contact grasping of target objects, improving the grasping success rate and reliability [59,60].

Two-finger and multi-finger grippers demonstrate efficiency and speed when repeatedly grasping the same type of object. Soft grippers have a lower design time and production cost than other actuators due to their comparatively simpler structure. Therefore, they are popular for simple tasks in industrial applications and include commercial products, such as Festo's tentacle gripper and mGrip from Soft Robotics Inc. [61–63].

In this context, a significant emphasis has been placed on enhancing output force and actuation speed when developing novel grippers. To achieve these objectives, many studies have integrated bistable mechanisms into the soft gripper design [51,64], which are characterized by two stable equilibrium states, representing local minima in the total potential energy. The incorporation of bistable mechanisms reduces control complexity, enables fast motions, and promotes energy conservation.

However, the functionality of these grippers still suffers from single grasping mode, enveloped grasping, or pinch grasping, limiting their applications and reducing their reliability in grasping small objects. Even in dual grasping mode [50], these grippers are still limited to object grasping, lacking the capacity for intricate manipulation.

2.2. Underactuated Anthropomorphic Soft Hands

Two-finger and multi-finger grippers face challenges in adapting to situations where the objects to be grasped are constantly changing, necessitating the use of a dexterous hand. In this context, the term "dexterity" refers to the ability of the hand to exhibit a wide range of postures. A hand is considered more dexterous when it displays higher variability, increasing its grasping diversity and in-hand manipulation involving different grasping patterns. For instance, small objects can be precisely grasped with a few fingers, while larger objects may require an enveloping grip, and thin objects can be grasped via a thumb opposition grip [4,5,65].

To adapt to a wider range of object shapes and sizes, soft hands have been designed and developed, inspired by the shape of the human hand. The human hand can manipulate objects of various morphologies and materials and can tune the pose and position of objects (in-hand manipulation) with high dexterity in limited spaces. Constructing dexterous anthropomorphic hands capable of autonomously grasping and manipulating objects has been an important aim during robotic system design.

Represented by the RBO hand, these developed soft hands are primarily designed based on the principle of passive adaptation to the shape of the object [8,52]. Passive adaptability enables the hand to dynamically adjust its surface in response to contact forces, achieving a shape-matching effect with the object. Enhancing shape-matching improves the contact area between the hand and the object, eliminating the requirement for explicit sensing and control [15,66,67]. This not only increases resilience against uncertainties in hand position, finger control, and environmental factors, but also enables a passive adaptive hand to establish contact in any direction without sustaining damage [53]. Consequently, the compliant hand can effectively utilize the environment as a guide during grasping motions, further strengthening grip robustness. Therefore, passive adaptability is key in soft hand design to achieve successful grasping under uncertainty [5,68].

Traditionally, achieving dexterous grasping capabilities in robotic hands involved complex multi-joint structures and intricate actuation mechanisms. In addition to requiring sophisticated perception and control systems, these hands are expensive and challenging to design [69]. A significant direction in soft hand design is to simplify the system and improve robustness. Underactuated soft hands utilize reasonable structural designs to control hand movements with fewer degrees of freedom (DOFs) than finger joints, reducing the complexity of the entire hand system while improving reliability [70].

Unlike rigid dexterous hands, soft hands do not require additional actuators to achieve human-like bending motions. For instance, Feix et al. introduced a configuration featuring a single actuator per finger, enabling the soft hand to effectively accomplish 31 out of 33 grasp postures outlined in the widely recognized Feix taxonomy [71]. Similarly, the RBO 2 hand, with a mere 7 DOFs, successfully executes 31 out of 33 grasp postures from the Feix taxonomy [52]. Furthermore, Fras et al. proposed a biomimetic hand design where each finger possessed only one DOF yet was still capable of performing a diverse range of human-like gestures and effectively grasping various objects [67].

2.3. Dexterous Anthropomorphic Hands

Underactuated hands have shown robustness in grasping tasks, providing cost-effectiveness and system simplification. However, their operational capabilities are inherently limited due to their underactuated nature. This presents a trade-off between robustness and functionality in robotic hand design. A notable limitation of underactuated soft hands is their restricted dexterity, particularly in manipulating and repositioning objects [19,54]. Moreover, the majority of soft hands, limited by soft mechanical design and manufacturing technologies, typically only exhibit several DOFs [5,52,56]. Underactuated fingers constrain the robotic hand's workspace, thus limiting its flexibility. This shortcoming hinders their broad application in complex, human-centric tasks. This is primarily attributed to the limited dexterity of soft actuators, which typically function as the fingers in soft hands. Most soft actuators have pre-defined motion trajectories, resulting in fixed trajectories for the fingers and overlapping motion limited to a singular point [72–74]. This paradox has spurred research into specific operational processes and the design of more dexterous hands, which are intelligent, multipurpose mechanical structures designed for a variety of tasks [4,6,20,75].

The common workspace between fingers is critical for in-hand manipulation. Designing multi-DOF soft fingers is a viable solution to address this, as demonstrated by integrating multiple actuators into a single finger [5,19,76,77]. Yet, this integration increases finger size and weight. Therefore, developing compact, lightweight multi-DOF soft fingers remains a valuable goal. Additionally, biomimetic dexterity, encompassing both appearance and kinematic functionality, is a key consideration in soft hand design, aiming for the effective handling of everyday objects.

Human-like designs with additional actuators can significantly enhance soft hand flexibility. Notable examples include the BCL-13 hand [20], the BCL-26 hand [5], the Blue hand [19], and particularly, the Blue hand with a total of 21 DOFs, able to perform all 33 grasp types in the Feix taxonomy and pass all Kapandji tests for thumb dexterity [19]. Another example is the dual-mode actuators, which enable fingers to execute both bending and twisting motions [66]. With ongoing advancements in soft robotics, soft humanoid dexterous hands are evolving towards more humanoid appearances and motion characteristics, as seen in the BCL-26 hand [5], the RBO Hand 3 [6], and others [30,75,78].

The thumb and thenar muscles play a vital role in hand dexterity (Figure 1b). The thumb is opposable, meaning it can move in opposition to the other fingers, allowing for precision grasping and manipulation of objects. This opposable movement is made possible by the coordinated action of the thenar muscles, which control the movements of the thumb. The thumb is the primary contributor to hand motion, achieving nearly 40% of overall hand movements [79]. The thenar muscles (Figure 1b) are significant for thumb movement and essential for various daily actions, such as grasping, gripping, pinching, clamping, twisting, and tying [4,80]. First, the thumb can oppose the other four fingers, which is a prerequisite for grasping objects [30]. Second, the thumb can simultaneously translate, rotate, and flex, which is an ability that other primate hands are incapable of [81]. During the object-grasping process, the thumb adapts its position based on the shape of the object. This necessitates the carpometacarpal (CMC) joint of the thumb to perform not only flexion and extension motions but also abduction and adduction movements. These various thumb motions enable different types of grasping and pinching actions [82].

Despite the importance of the thumb, its motion differs significantly from that of the other fingers, and research on the mechanical design of the thumb is limited [83]. Many modular designs still treat the thumb the same as the other fingers, merely placing it in an opposing configuration [84], severely limiting its functionality and affecting the grasping ability of the entire hand. Recently, studies have revealed a flexible thumb with an active thenar, improving the grasping ability of the soft hand [4]. However, practical considerations, such as space constraints for actuators weight and cost limitations, challenge the implementation of multiple DOFs in the thumb.

Previous research has often overlooked the functionality of the palm, focusing primarily on soft finger designs. The hand muscles facilitate palm flexibility, allowing it to bend and form a concave shape, which is essential for grasping objects. The three key arches, namely the longitudinal, distal transverse, and oblique, achieve dexterous palm motion (Figure 1b) [85]. Many soft, humanoid, dexterous hands replace the palm with rigid materials, lacking actuation and limiting their grasping and manipulation capabilities. To address this, researchers have incorporated flexible actuators into the palm, enabling active palm-like functions. For instance, Wang et al. proposed an active palm with pneumatic actuation to enhance hand dexterity [78,86], while the RBO Hand 2 and 3 feature activatable anthropomorphic palms [6,52]. Experimental results have demonstrated that the active palm in anthropomorphic hands is a key factor in improving the performance of thumb opposition and envelope grasping [75,87]. A comparison of the main features of various types of soft hands is presented in Table 1. Examples of nonanthropomorphic grippers, underactuated anthropomorphic hand, and anthropomorphic dexterous hand are presented in Figure 2.

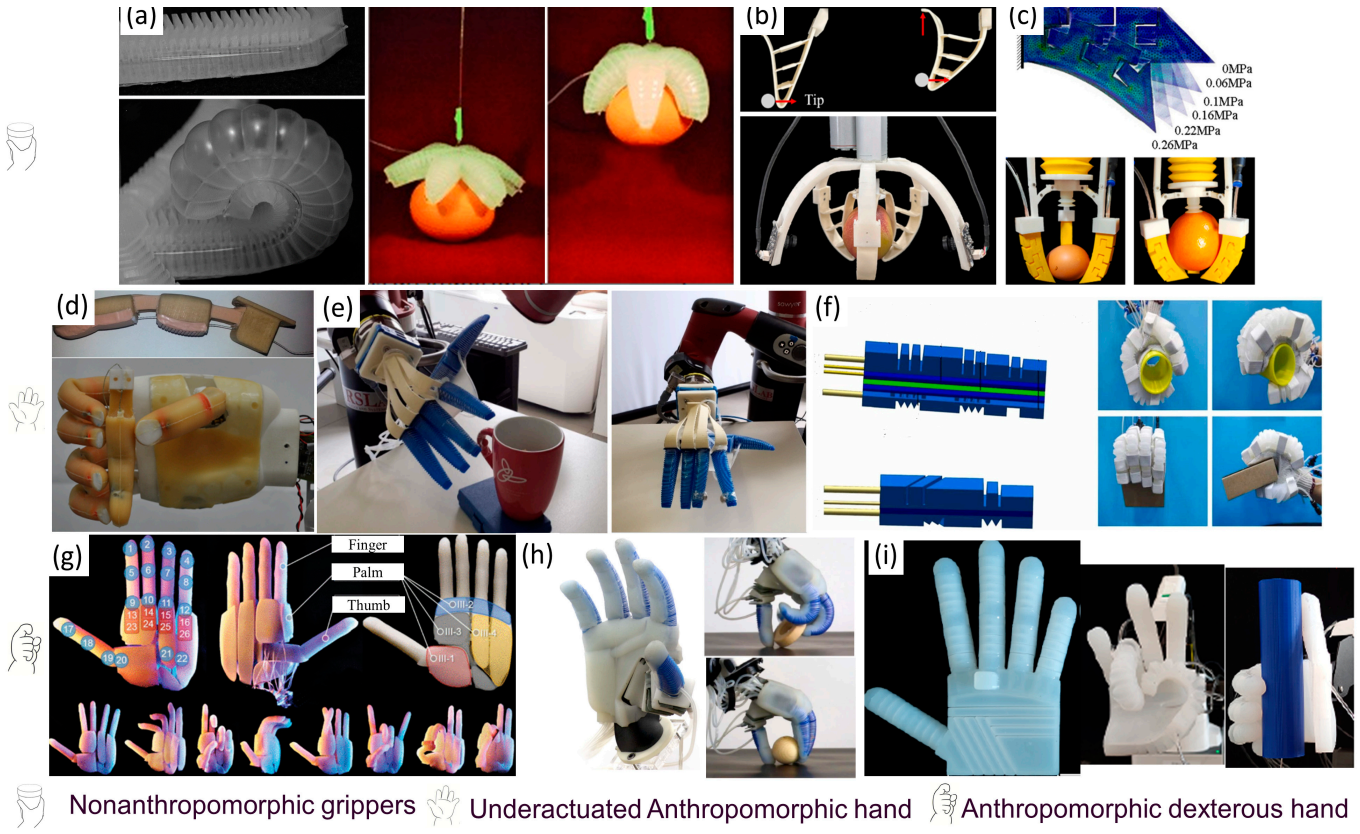


Figure 2. Development of various types of soft hands. Top: nonanthropomorphic grippers, (**a**) starfish-like grippers [2], (**b**), soft gripper for both safe grasping and non-destructive firmness evaluation [88] (**c**), middle, underactuated anthropomorphic hand, (**d**), UC soft hand with compact twisted string actuation mechanism [89], (**e**), soft hand with magnets to robustify the performance [90] (**f**), soft glove with four kinds of rehabilitation postures [91], and bottom: anthropomorphic dexterous hand (**g**), BCL-26 soft hand with 16 DOFs [5], (**h**), RBO Hand 3 with a dexterous opposable thumb [6] (**i**), soft hand with active palm [75].

2.4. Methods to Enhance Grasping and Manipulation Performance

To augment the functionality of soft humanoid hands, researchers have embarked on innovative design explorations aimed at expanding their application range while concurrently enhancing their flexibility. A predominant challenge in the realm of soft hands is their limited output force [92,93]. This constraint directly impacts their carrying capacity,

narrowing the spectrum of objects they can effectively grasp and thereby curtailing their application breadth. To address this, the integration of variable stiffness elements into soft hand systems has been proposed [94,95]. Activating these elements increases the structural stiffness of the gripper, aiding in the lifting of heavier loads. These elements bolster the carrying capacity of soft hands without markedly compromising their compliance and adaptability when inactive. Particle jamming is the most popular approach for variable stiffness due to its safety and easy availability [96,97]. Other variable stiffness methodologies include interference-based methods [98], motor-based methods [99], variable modulus-based methods [100], electromagnetic field-based methods [101], and phase change material-based methods [102]. Examples of stiffness-based methods to adjust grasping and manipulation performance are presented in Figure 3.

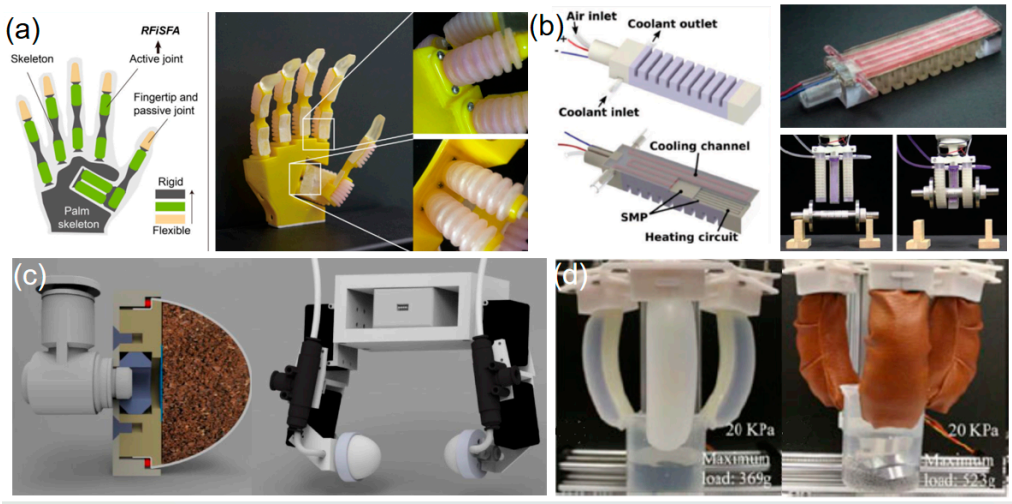


Figure 3. Rigid−flexible integration and variable stiffness design of soft grippers and hands. (**a**) Rigid−flexible integration configuration [33], (**b**), integration of shape memory polymer for variable stiffness [103] (**c**), particle jamming method for two fingered−gripper (**d**), particle jamming method for three−fingered gripper [96].

Despite these improvements, the maximum carrying capacity of soft hands still lags behind that of conventional rigid grippers and human hands. For instance, the pneumatic soft hand integrated with shape memory polymers, as developed by Zhang et al., can lift a 1.5 kg dumbbell using three fingers—a notable achievement for a soft gripper, yet still trailing behind its rigid counterparts (Figure 3d) [103]. The incorporation of variable stiffness elements often introduces additional actuation methods and elongates response times.

In recent years, some researchers have explored the fusion of rigid and soft structures, employing collaborative mechanisms to synergize their respective advantages, thereby achieving superior overall performance [32]. These rigid–soft coupling designs have demonstrated significant promise. For example, the single–stable rigid–soft coupling gripper proposed by Tang et al. can securely grasp an egg and stably lift an 11.4 kg dumbbell [104]. Liu et al. developed flexible hybrid pneumatic actuators for soft hand fingers [32]. The soft humanoid hand exhibits satisfactory comprehensive performance, including fast response, substantial grasping force, affordability, lightweight construction, and ease of fabrication and repair. Nonetheless, these designs confront challenges, such as not fully capitalizing on the high output force of rigid structures and the flexibility of soft structures. Moreover, current rigid–soft coupling gripper designs often feature complex and bulky structures, which substantially limit their compliance. Furthermore, high stability is imperative for robotic grippers, as soft robotic grippers frequently undergo deformation or prolonged vibrations due to external forces like gravity or impact, potentially impairing their operational efficiency and precision.

Environments containing lubricants like water or oil can significantly impact the performance of soft humanoid hands. The frictional interaction in such scenarios is crucial for stable grasping. Human fingertip skin undergoes various degrees of stretching during object grasping, with ridge patterns bolstering grasping ability [105,106]. In wet environments, fingerprints enhance the grasping area, thereby improving the success rate [107,108]. This mechanism differs from the adhesive effect observed in tree frog toe pads or gecko claw setae, which operate at the nanoscale [109,110]. Human fingerprints are relatively macroscopic and primarily leverage frictional changes to augment grasping. Hao et al. indicated that fingerprint-like surface textures significantly enhanced the pinch-grasping ability of soft humanoid hands in water and oil lubrication conditions, surpassing the performance on smooth surfaces [111]. Additionally, applying a concentrated hyaluronic acid solution to the surfaces with fingerprint-like textures enabled the soft hand to grasp a variety of common medical instruments, marking a substantial improvement over smooth surfaces [112].

3. Tactile Perception

A dexterous anthropomorphic hand lacking a tactile sensing feedback mechanism falls short in comparison to the human hand, as it lacks the ability to autonomously interact with its surroundings. This deficiency hinders the ability to regulate contact forces accurately and execute precise manipulations [113]. Substantial efforts have been directed towards developing external perception capabilities for soft hands, with tactile sensing identified as crucial for safe, refined object grasping and manipulation [114,115].

Human interaction with the external world is largely mediated through tactile sensing via the skin, the body's largest sensory organ, which plays a vital role in survival, exploration, and response. Similarly, tactile sensors are fundamental in robotics for achieving biomimetic sensing and intelligent interaction. These sensors convert tactile stimuli into electrical signals that computers can interpret, holding significant potential in human healthcare, biomimetic robotics, and human–machine interaction. Recent advancements in flexible electronics and nanotechnology have facilitated the development of tactile sensing technologies that emulate human skin characteristics [116,117]. Embedded sensors and electronic skin (e-skin) are the most applied strategies to provide tactile perception for soft hands. Several examples of soft hands with integrated perception devices are presented in Figure 4.

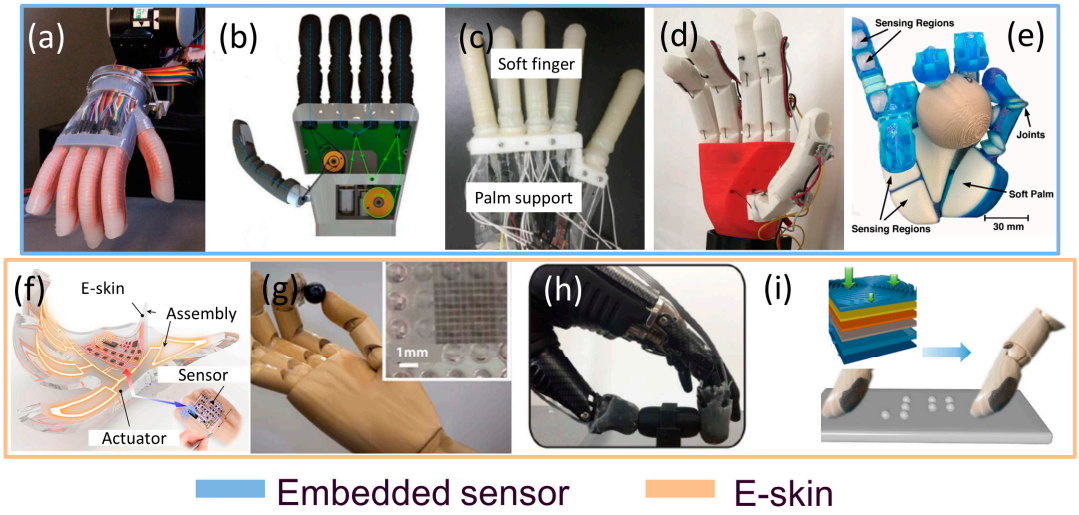


Figure 4. Tactile perception of anthropomorphic soft hands with embedded sensor (**a**), stretchable optical waveguides-based sensor [118] (**b**), capacitive sensor [119] (**c**), flexible optical fiber-based sensor [120] (**d**), air pressure sensors [121] (**e**), distributed soft sensing unit [30] and e-skin (**f**), e-skin for both pressure sensing and actuation [122] (**g**), capacitive e-skin for detecting normal and tangential forces [123] (**h**), mechanoreceptor- and nociceptor-based e-skin for neuromorphic tactile perception [124] (**i**), fingerprint inspired triboelectric e-skin for texture perception [125]).

3.1. Embedded Sensors

A direct approach to equipping soft hands with perception capabilities involves the integration of sensors onto their surfaces. By incorporating sensors directly onto the soft hand's exterior, it becomes possible to capture and interpret information about the surrounding environment. These sensors can be designed to detect various stimuli such as pressure, temperature, proximity, and even tactile feedback. For instance, tactile sensors have been integrated into soft actuators and hands for closed-loop control of grasping force [30,126], while novel soft sensors capable of detecting contact forces and object curvature during grasping have been proposed [127]. Stretchable optical waveguides were applied as embedded sensors in a soft hand system to detect curvature, elongation, and force during object interaction (Figure 4a) [118]. These optoelectronic strain sensors, characterized by ease of fabrication, chemical inertness, and low hysteresis, exhibited the ability to act as multi-modal sensors. Zhou et al. designed and developed a soft hand equipped with soft sensors using 3D printing for effective integration with myoelectric control systems (Figure 4d) [121].

Marasco et al. developed an artificial sense of touch in a prosthetic hand equipped with pressure sensors, providing sensory feedback via a force-tactile interface [128]. This interface stimulated sensory nerves redirected to the residual limb skin, applying proportional pressure. Additionally, e-skin can enhance prosthetics by providing sensory perception and interaction capabilities for amputees and individuals with nerve damage (Figure 4e) [21].

A novel dual-purpose design has been proposed for soft fingertips to enhance the performance of in-hand manipulation, presenting a unique approach for delicately manipulating soft objects without causing damage [129]. This innovative approach involves equipping robotic hands with soft fingertips that possess both tactile sensing and active shape-changing capabilities. By actively manipulating embedded air cavities, the fingertip demonstrates precise control over the in-hand manipulation of soft objects, aided by pressure feedback control. Additionally, a 3D-printed soft hand has been developed for prosthetic applications, incorporating flexible sensors that are compatible with advanced myoelectric control systems such as pattern recognition control and simultaneous proportional control [130]. By integrating flexible position sensors into the fingers, the hand can monitor finger positions to prevent self-collisions, enabling smoother and more intuitive transitions between gestures. The combination of various gestures empowers the hand to perform multi-stage grasping and manipulate multiple objects simultaneously.

For sophisticated manipulation, it is necessary to recognize the object pose estimation observed in human fingers, which remains a fundamental yet challenging task in robotics. Various methods for hand pose estimation (HPE) [131] and hand–object pose estimation (HOPE) [132,133] have been developed, mirroring human manipulation strategies. Inspired by proprioception, embedded cameras and deep learning architectures have been proposed for object recognition in soft fingers. Liu et al. presented a soft finger design that integrated inner vision and kinesthetic sensing to replicate the object pose estimation capabilities observed in human fingers [115]. The proposed framework offered a comprehensive solution that leveraged raw images captured by the soft fingers to estimate the pose of objects held in the hand, providing an end-to-end approach for accurate object pose estimation. The framework underwent testing with seven objects, achieving impressive results with a pose error of 2.02 mm, an angle error of 11.34 degrees, and a classification accuracy of 99.05%.

While these solutions demonstrate the advantages of tactile feedback in soft grippers or fingers, they primarily provide aggregated contact information. Distributed sensor networks can offer spatial information on contact events for a more comprehensive understanding. He et al. proposed a soft hand featuring an active palm and tactile perception enabled by distributed pneumatic sensors integrated into both the palm and fingers [30]. Leveraging multi-material 3D printing enabled the direct printing of tactile sensors on the hand, contrasting with traditional tactile methods that necessitated separate attachment

as part of multiple fabrication steps. The presented hand successfully executed 32 out of 33 Feix taxonomic parameters for grasping and all 11 Kapandji tests.

3.2. Electronic Skin (E-Skin)

The concept of electronic skin (e-skin) draws inspiration from the sensory and mechanical properties of human skin, with the goal of developing electronic devices that can emulate these characteristics. E-skin is designed to replicate the functionalities of human skin, such as the ability to sense touch, temperature, pressure, and even humidity. The development of e-skin involves the integration of various components, including flexible and stretchable materials, sensors, and electronic circuits. These components work together to create a thin and flexible electronic layer that can be applied to the surface of objects or even directly onto the human body. E-skin, with capabilities comparable or superior to human skin, holds vast potential in fields such as intelligent robotics [134,135], wearable medical devices [136,137], and human–machine interaction [122,138]. Additionally, e-skin can enhance prosthetics by providing sensory perception and interaction capabilities for amputees and individuals with nerve damage [21].

Although various e-skins have been developed for monitoring pressure, recent innovations involve integrating individual tactile force sensor pixels into soft robots. Yamaguchi et al. developed a soft hand with integrated e-skin pressure sensors, focusing on incorporating strain effects into both the sensor and the overall mechanical system [116]. The e-skin demonstrated insensitivity to strain resulting from structural actuation bending and the ability to monitor tactile force distribution when the soft hand held an object.

Monitoring object sliding within the soft hand is helpful for grasping by providing feedback to adjust the gripping force and prevent slippage. While human hands naturally possess this capability, current robotic hands lack it because of the complexity of integrating various sensors. Successful integration can significantly improve the performance of soft hands in human–machine interaction applications. Two primary challenges arise: integrating sensors into high-strain areas without compromising dexterity and optimizing sensor sensitivity to match execution force and detectable threshold pressure during object contact. Soft hands integrated with e-skin can monitor tactile pressure, temperature, and sliding during grasping and manipulation without compromising robot softness [113]. In addition to force measurement, object sliding or slipping when held in a soft hand can be tracked by assessing the time delay of the tactile forces detected by the sensor array.

Advancements have produced e-skins capable of sensing temperature, pressure, vibration, and strain, similar to human skin [139]. Various biomimetic strategies have been employed, utilizing interlocked microstructures combined with resistive [140], piezoresistive [141], ferroelectric [142], triboelectric [143], or capacitive [144] sensor arrays. These multifunctional sensing systems improve sensitivity, reduce response time, and increase linearity to enhance the perception performance of soft hands. However, distinguishing different stimuli remains challenging since soft hands are exposed to various objects in different posture and loading conditions.

3.3. Multi-Dimensional Force Perception and Multi-Modal Sensing

Human skin can perceive tactile stimuli, distinguish between normal and shear forces, and discern the temperature, hardness, and roughness of touched objects [145]. Emulating this capability in humanoid dexterous hands is crucial for accurately identifying grasped objects using tactile feedback from sensors. Therefore, designing tactile sensors with 3D force perception and multi-modal sensing capabilities is significant for enhancing the intelligence of dexterous hands. Tactile sensing is essential for providing contact properties such as pressure, motion direction, location, and surface hardness/texture [146]. This is particularly important for anthropomorphic soft hands, where internal torque sensing may not always be feasible due to design or cost constraints. The real-time measurement and differentiation of force direction, typically normal and shear, are necessary for providing slip and surface property information, which cannot be obtained through traditional wrist

force, torque, and proprioceptive sensors in current robots [147]. To achieve the advanced capability, array based and multi-layer based design strategies (Figure 5) are usually applied in conjunction with carefully functional materials.

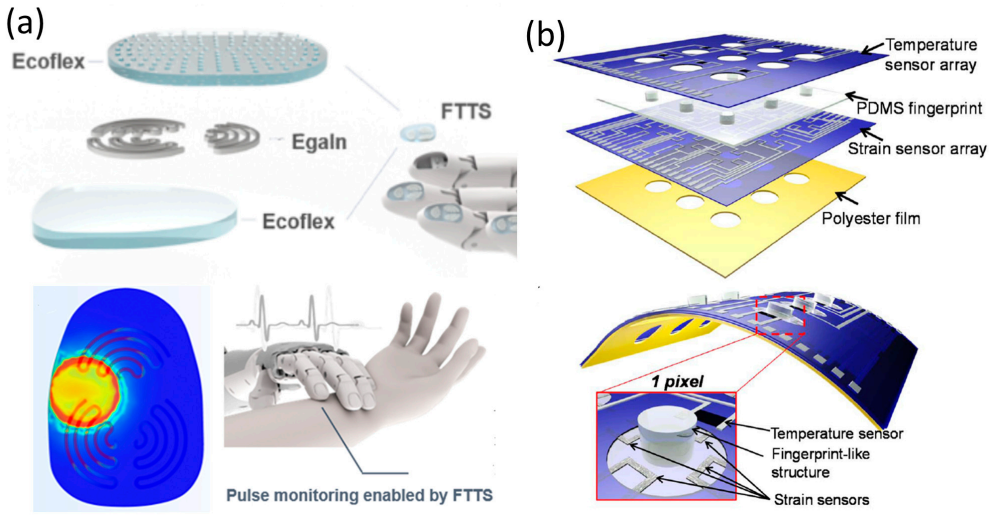


Figure 5. Array-based or/and multi-layer based design strategy for multimodal soft sensors. (**a**) Fingerprint-inspired array-based e-skin for pressure and position detection (Highlighted area indicates corresponding COMSOL simulation of forces applied) [148] (**b**), soft senor with both array and multi-layer structure for three dimensional force, slip, and temperature perception [149].

Boutry et al. developed an e-skin capable of differentiating normal and shear forces by mimicking the mechanism of the ridges and mechanoreceptors in human skin (Figure 4b) [123]. The capacitor sensor array was sensitive to various stimuli, and the nature of unknown stimuli could be assessed by analyzing recorded signals against a known library of stimulus–response curves. This capability was realized via a 3D configuration that replicated the interconnected dermis–epidermis interface present in human skin. Nevertheless, these systems come at the expense of hand manipulation speed and controller performance. Qu et al. proposed the utilization of a flexible triboelectric tactile sensor (FTTS) designed in a shape inspired by human fingerprints (Figure 4i) [148]. This sensor incorporated eutectic gallium–indium (EGaIn) liquid metal and silicone materials, operating on the principle of a triboelectric nanogenerator. Using three independent fingerprint-like channels, the sensor could detect pressure intensity and position, simulate passwords, identify materials, and monitor pulses.

Recent popular strategies for fabricating multi-modal tactile sensors include integrating various sensing units [150,151], designing sensing arrays to decouple different types of signals [149,152], developing novel materials able to simultaneously sense multiple stimuli [153,154], and designing novel structures [143,148]. Multi-modal sensors with decoupled sensing mechanisms allow a robotic hand to acquire more precise tactile information about the target object, facilitating dexterous object manipulation. They also benefit accurate real-time health monitoring, allowing for the separate measurement of different physiological parameters, such as body temperature and movement, improving the accuracy and safety of the human–machine interface. Mechanism and output signals of flexible sensors with capabilities of multi-dimensional force perception or multi-modal sensing are summarized in Table 2. Future robots will require complex feedback regarding force, temperature, and touching surface properties for tasks trivial to humans, like grasping a glass or inserting a key into a lock, making the development of a multi-modal complex sensing system an inspiring and challenging research topic.

Table 2. Flexible sensors with capabilities of multi-dimensional force perception or multi-modal sensing.

Output	Mechanism	E-Skin	Ref
Force, sliding, temperature	Resistant	√	[116]
Curvature, elongation, force	Optical waveguides-based		[118]
Normal forces, and tangential	Capacitive		[123]
Force, texture	Triboelectric		[125]
Pressure, position, material	Triboelectric	√	[148]
Normal and shear force	Piezoresistive		[155]
Temperature, vibration, shear force, normal force	Thermoresistive, piezoresistive, piezoelectric		[156]
Strain, temperature	Resistant, thermoresistive		[157]
Normal and shear force, sliding	Capacitive, resistant	√	[158]
Three-axis force	Resistant		[159]
Location, intensity	Piezoresistive		[160]
Pressure, sliding	Capacitive, triboelectric		[161]
Sliding, pressure	Piezoresistive, triboelectric	√	[162]
Sliding, pressure	Piezoresistive, triboelectric	√	[163]
Temperature, pressure	Thermoresistive, piezoresistive		[164]
Strain, pressure, and temperature	Capacitive, resistant, thermoresistive		[165]

The advancement of flexible electronics and nanotechnology has driven the development of tactile sensing technology, enabling it to simulate the characteristics of human skin. Tactile sensors are crucial for robots to achieve biomimetic perception and intelligent interaction, as they convert tactile stimuli into signals that computers can interpret. This technology has the potential to play an important role in human healthcare, biomimetic robots, and human–computer interaction. Soft humanoid hands require tactile perception to ensure safe interaction with objects. By using integrated tactile sensing devices, soft hands can perceive and interpret tactile information of external objects to adjust contact forces and perform precise operations. This not only improves the interaction ability between the soft hand and the environment but also increases the flexibility and reliability of the robot in various tasks. The further development of tactile sensing technology will further enhance the application potential of soft humanoid hands in fields such as medical rehabilitation, home services, and industrial flexible grasping.

4. Machine Learning in Soft Hands

The remarkable adaptability of the human hand in performing various tasks is a testament to its biomechanical superiority, which is further enhanced by the learning and memory mechanisms of the nervous system. The goal of the next generation of soft hands is to achieve the capability of accurately perceiving their surroundings and making correct decisions in response to stimuli. The advancements in machine learning have proven beneficial in increasing the accuracy of tactile perception and improving the decision-making strategies of soft hands during their interactions with different environments. Similarly, soft hands can benefit from incorporating machine learning techniques to address their inherent limitations, such as nonlinearity and hysteresis, which arise from structural compliance, material viscoelasticity [166,167], inconsistent outputs during loading and unloading cycles, and higher complexity due to factors like drift and high DOFs, challenging the mathematical modeling and calibration of soft hands and grippers.

Machine learning, renowned for its efficacy in solving nonlinear problems across various fields [168,169], has been increasingly applied to soft robotics. Its applications extend to soft sensor calibration [170,171], soft actuator position control [172,173], and more intricate tasks like grasping and in-hand manipulation [69]. Research indicates that machine learning-based methods have successfully mitigated many of the current challenges faced by soft robotic hands. A schematic of an anthropomorphic soft hand interacting with the environment with machine learning models is presented in Figure 6.

Sensor calibration aims to accurately estimate physical stimuli, such as strain and stress, from soft sensor inputs, such as resistance and capacitance, using the Artificial Neural

Network (ANN), k-nearest Neighbors (kNN), Recurrent Neural Network (RNN) [167,174], Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Long Short-Term Memory (LSTM) models. These models are widely applied to evaluate grasping information, such as object recognition, grasping stability, and hand pose [175]. To address the hysteresis characteristics in output signals, both mathematical models and data-based methods have been used for optimization [176]. Data-based approaches often employ machine learning algorithms and convex optimization to fine-tune hysteresis model parameters [167]. Luo et al. designed a bioinspired soft sensor array (BOSSA) via theoretical and experimental investigations into the triboelectric effect and cascaded electrodes [177]. Using a data-driven algorithm, multilayer perceptron, the BOSSA was capable of environmental self-awareness, with pressure- and material-sensing abilities. Deep learning, well-established in fields like computer vision and natural language processing [178], has also been applied to soft sensor research. For instance, Navarro et al. utilized feed-forward neural networks and transfer learning to calibrate soft pneumatic mechanosensors, comparing results with those from numerical methods like the finite element method [179].

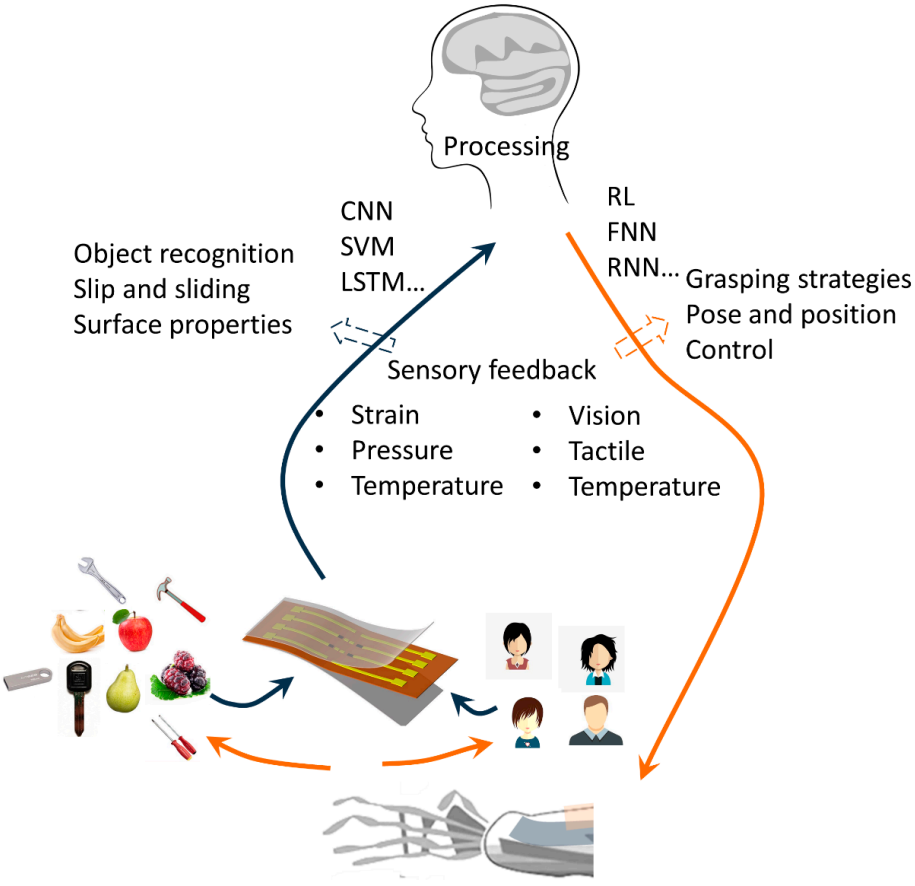


Figure 6. Schematics of an anthropomorphic soft hand interacting with the environment with machine learning models.

Inputs from sensors are processed by machine learning models, usually the feed-forward neural network (FNN), RNN, and CNN, to estimate pose/position and to generate control strategies for the proprioception and motion control of soft grippers and hands [22,180]. Machine learning has also been useful in soft robotics for generating grasping poses for unknown objects [181,182]. Demonstration learning has been combined with reinforcement learning to transfer grasping capabilities from human operators to robotic systems [183]. Dexterous robotic hands with multiple fingers are capable of an extensive range of actions, and their morphological resemblance to the human hand presents significant potential for expediting robot learning. Mandikal et al. introduced an innovative method for acquiring proficiency

in robotic grasping by leveraging human–object interactions available in openly accessible videos [184]. Using deep reinforcement learning, it can easily scale to new objects without collecting human demonstrations. Learning-based techniques have also facilitated the transfer of human-operated soft hand response strategies to robots for grasping new items in human–robot handover scenarios [185]. These advancements highlight the synergy between machine learning methods and the inherent adaptability of soft hands to unknown environments.

A deep learning-based method has been developed to address the challenge of predicting whether the grasp will be successful in soft hands [186]. This framework utilizes two neural architectures: a classifier for the a-posteriori detection of failure events and a predictor that uses readings from Inertial Measurement Units (IMUs) to estimate object sliding. By leveraging these neural architectures, the framework can effectively anticipate grasp failures in soft hands before they occur. Santina et al. proposed a strategy that mimics human motion to achieve autonomous soft hand grasping [182]. This approach employs a deep neural network classifier to analyze the visual information of the object to be grasped. Based on this analysis, the classifier predicts the action that a human would likely perform to achieve the desired goal. The predicted action is then used to select one of several human-inspired primitives, combining anticipatory actions with touch-based reactive grasping. Research on machine learning related to anthropomorphic soft hands is shown in Table 3.

Table 3. Research on machine learning related to anthropomorphic soft hands.

Machine Learning Methods	Learning Features	Implemented Functions	Performance Index	Ref
ANN	Reducing the dependence on feature engineering	Texture recognition	Accurary: 92.5% to 93.33%	[125]
RNN	Hierarchical recurrent sensing network	Estimating pressure responses and localizing the position	Accuracy: 85%	[171]
CNN, RNN	States and actions based on feedback from the environment	Controlling the position of soft robotic arm	Average error: 4.8 mm	[172]
Bayesian optimization	Performance of IPMC	3D printing of IPMC actuators and the motion control of the crawling robot	Maximum possible distance:95%	[173]
DNN	Data collected by probe terminal electrodes	Position recognition and pressure sensing	Accuracy: 98%	[174]
Policy learning method	High-resolution tactile inputs	Predicting future grasp actions	Accuracy: 76–98%	[175]
Multilayer perceptron model	Contact signals	Object Recognition of Robot Hands	Accuracy: 98.6%	[177]
ANN	Changes in airflow, volume changes	Predicting contact location and force magnitude	Average error: 1.94–2.88 mm	[179]
ANN	RGB images, RGB-D images, or point clouds	Object Pose Estimation for Robotic Grasping	-	[181]
CNN	RGB images	Generating grasping poses for unknown objects	Accuracy: 81.1%	[182]
CNN	State information	Flexible operations of RBO Hand 2	-	[183]

This section demonstrates how soft hands can partially replicate human-like movements in grasping tasks by imitating the shape, structure, and function of human hands, providing flexibility and operability. The article predicts that these soft hands, designed to mimic human dexterity, will become the focus of robot hand development and have broad market prospects in industrial flexible grip solutions, medical rehabilitation, home services, and other fields. Future advancements may stem from further sensor and actuator integration, aiming to develop soft hands that can rival the capabilities of biological organisms.

5. Outlook

5.1. Potential Applicaitons

In the field of healthcare, the application of the anthropomorphic soft hand is very extensive. For example, in surgery, soft robotic arms can cooperate with doctors to perform minimally invasive surgery, allowing for more precise operations and reducing harm to patients. In addition, soft robotic arms can also be applied in rehabilitation assistive devices to assist rehabilitation patients in self-care training or provide more intelligent assistive tools for disabled individuals to improve their quality of life.

In industrial production, anthropologic soft hands can collaborate with human workers to complete the assembly work of small and vulnerable parts. This type of soft robotic

arm has a strong adaptability to meticulous operations, which will be of great help in the production of electronic components, medical devices, and other products that require careful operation. In addition to the production field, soft robotic arms can also be applied in hazardous environments, such as radioactive areas or chemical processing, to avoid direct human operations in high-risk environments.

In the field of personal assistance, the anthropomorphic soft hand also has broad application prospects. For example, it can be applied to assist elderly people in their daily lives, performing simple and common actions such as picking up items, wiping the table, etc. In addition, soft robotic arms can also be designed to take care of people with disabilities, such as helping them complete self-care activities, and even engaging in intelligent communication and interaction.

Overall, the application of the anthropomorphic soft hand in fields such as healthcare, industry, and personal assistance will have a profound impact in practical scenarios. It will improve work efficiency, reduce human errors, promote a safer working environment, and improve quality of life in the fields of healthcare and personal assistance. The development of soft robotic arms will strongly promote the advancement of robotics technology and become one of the key technologies in the future.

5.2. Challenges and Future Directions

As the end effector, robotic hands determine essential functions for the robotic system, like grasping and in-hand manipulation. Soft, dexterous hands adapt actively or passively to environmental changes, compensating for rigid hand limitations. These grippers and hands excel in adaptability and interaction, executing tasks gently and securely, even with delicate items, in unstructured settings. The goal of robotic gripper design is to replicate human-inspired dexterity for autonomous object manipulation. Yet, despite the advantages of soft, human-like, dexterous hands, they still present significant disparities and limitations compared to their human counterparts. Therefore, addressing these challenges during continuous soft-hand development is a priority.

Most underactuated soft grippers and hands typically exhibit a single grasping mode when handling objects of varying sizes. The dependability of grasping diverse types of objects, particularly small ones, is frequently limited by the mismatched or insufficient contact area. In addition, underactuated hands often lack sensing capabilities, which means their anti-interference ability during the grasping process is a concern.

Dexterous soft hands with multiple joints and 20 or more DOFs require complex mechanical structures, presenting a significant challenge for design because of the compact, narrow digit space, especially the thumb. This scenario is exacerbated by integrating a considerable number of sensing units into the main configuration. Researchers face challenges in the industrialization and commercialization of dexterous soft hands due to the trade-off between their overall performance and the time and cost of design.

Compared to rigid and human hands, the load capacity of current soft hands is relatively low, hindering more extensive application. Although development in material science provides potential solutions to this problem, further investigation into improved variable stiffness methodologies to enhance grasping performance is necessary. In addition, adding friction layers with specially designed microstructures may also contribute to stable grasping in various environments.

Environmental perception plays a pivotal role in manipulation tasks. Several tactile sensors have been developed for specific parameters, demonstrating high performance comparable to or even surpassing that of human skin. Nevertheless, creating tactile sensors that encompass all the properties of human skin remains a formidable challenge. The development of enhanced decoupling mechanisms and methods is vital for multi-module sensors to ensure the production of unaltered signals and the accurate restoration of stimuli.

Machine learning has been employed to capture human gestures/poses and control soft hands to achieve object grasping and in-hand manipulation. While numerous promising results have been reported, several challenges persist, including the proper training of

general machine learning models and addressing the nonlinearities inherent in soft systems. Overcoming hurdles, such as the need for a substantial amount of data, unexpected error sources, and the necessity for real-time measurements and controls, is crucial for further advancements in this field. To complete tasks in unknown or complex environments, a soft robotic arm requires a high level of perception ability and intelligent decision-making systems. However, embedding highly integrated sensing systems and intelligent algorithms into software materials to achieve the environmental perception, data processing, and decision execution functions of robotic arms is a complex engineering task. Among them, the ability to process a large amount of sensor data in real-time and make rapid and accurate responses is currently the bottleneck of technological development.

Furthermore, a commonly overlooked issue is the fabrication errors associated with soft hands. During soft hand fabrication, 3D technology is commonly used for casting. However, the fabrication accuracy falls short when compared to rigid counterparts. These manufacturing flaws significantly reduce the deformation, bending, and output force stability of anthropomorphic soft hands. Due to the close collaboration between soft robotic arms and human workers, they must have extremely high safety performance to avoid harm to people or objects during operation. However, ensuring the reliability and low failure rate of soft robotic arms, especially when experiencing frequent deformation or contact with different objects and surfaces, remains a challenge in technological development. The wear and tear, aging, and maintenance strategies of soft robotic arms are also current issues that need to be overcome.

The activities of soft robotic arms typically require external energy sources, such as pneumatic or hydraulic systems, which are often bulky and inconvenient to carry. This greatly limits the application of soft robotic arms in situations where there is no fixed energy supply point. Meanwhile, the energy conversion efficiency of soft robotic arms is low when undergoing multiple bending and stretching movements, which may lead to excessive energy consumption, thereby limiting their continuous working time and practicality.

With the continuous progress of robot technology, it is expected that future robot soft hands will integrate more advanced multimodal perception systems and incorporate innovative materials and intelligent structures to improve load capacity and adaptability to variable stiffness. In addition, new design and manufacturing technologies will greatly improve the performance of soft hands and reduce production errors. By utilizing advanced machine learning and adaptive control algorithms, soft hands will be able to simulate human hand movements more naturally and be applied in increasingly expanding fields such as advanced manufacturing, service robots, medical assistance, and even disaster response scenarios. At the same time, the sustainability and maintenance issues of soft hand design will also be given attention, and improvements in user interface and interaction performance will make soft hands more user-friendly. These innovations will not only greatly expand the application scope of robotic hands, but also have the potential to change the way humans and robots interact, improving the efficiency and safety of human–machine cooperation. In the future, robot soft hands are expected to achieve more precise operations, unlock new application prospects, and become indispensable assistants in human life and work.

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