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Large-scale iontronic skins with neural-hierarchical processing architecture

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Abstract

The human skin can encode and gather signals from over 200,000 afferents, providing high spatiotemporal-resolution sensations to enable fine touch and to prevent skin injury. Existing robotic skins typically employ a serial architecture to readout multichannel signals, while such an architecture becomes incapable when a skin has thousands of receptors, resulting in readout latency, signal crosstalk, and bandwidth consumption. Here, we introduce a large-scale neural-hierarchical iontronic skin (NI-skin) with >10,000 sensors that mimics the hierarchical processing architecture of the tactile nervous system, transmitting tactile information in layers via signal encoding, convergence, and cognitive modeling. The position-encoding of the frequency-dependent iontronic receptors enable parallel transmission with ultralow latency and suppressed crosstalk, while the backend convergent compression minimizes bandwidth, achieving an 800 μm spatial resolution and a 10.6 ms temporal resolution. We demonstrate that robots equipped with our system can perform challenging tasks, including fine tactile interactions and the perception of pain-related mechanical stimuli for proactive injury avoidance. This technology provides a large-scale tactile system with high spatiotemporal resolution, paving the way for humanoid robots to achieve human-level perception and manipulation.

Keywords: Iontronic skin; tactile sensing; neuromimetic sensory system; spatiotemporal-resolution; robot interaction.

Introduction

The rapid development of artificial intelligence and sensing technologies has propelled remarkable advances in intelligent humanoid robots ^[1,2]. One of the ultimate goals of human-centered robotics is to achieve human-level perception and manipulation ^[3,4]. The human skin, which is the outer covering of the human body with an area of $\sim 1.5 \text{ m}^2$, is distributed with more than 200,000 mechanoreceptors ^[5,6]. The myriad mechanoreceptors can collect tactile information without interferences or latency to provide timely and high spatiotemporal-resolution information of touch ^[7-9]. Replicating such sensory capabilities of the human skin in artificial sensors has attracted considerable attentions. Although existing sensors can be made to be more sensitive than a single mechanoreceptor, when integrating thousands or more sensors together, the sensor array cannot operate without delay or inter-unit interferences in signals ^[10-14].

Existing artificial skins or sensor arrays mostly employ an array structure with shared electrodes (rows and columns) that can effectively simplify wiring for large-scale sensor array ^[14-19]. Multichannel signals are often read out through a serial architecture of time-divisional multiple access (TDMA) ^[14-16], where individual elements are read sequentially and periodically. Such a serial readout architecture, however, introduces a strong latency and switching noises ^[20,21], making the architecture incapable for highly dense sensor array containing thousands of sensing units.

The human tactile sensory system encodes temporal spikes through primary sensory neurons, transmitting information via parallel neural pathways ^[6,22]. The posterior wedge nucleus and spinal cord converge and relay this information to the somatosensory cortex ^[8]. Pioneering studies have mimicked the human sensory system by converting analog responses of sensors into spike trains ^[9,20,23-26], with spike frequency or shape to reflect tactile features. However, in such systems, each sensing

56 element requires a dedicated circuit to translate tactile signal into spikes, and decoupling the spikes
57 from multiple sensors is highly challenging. Therefore, this approach is not suitable for large-scale,
58 high-density sensor array. Other studies have proposed frequency-modulated encoding that effectively
59 improves parallel perception and transmission, using carrier frequency for spatial position and
60 amplitude for sensing intensity [21,27]. Nevertheless, it remains a major challenge to embed a large
61 number of sensors in a limited frequency bandwidth, and to optimize transmission architectures for
62 large-scale, high-resolution tactile perception.

63 To tackle this challenge, we introduce a large-scale neural-hierarchical iontronic skin (NI-skin)
64 system that imitates the hierarchical processing architecture of the human tactile nerve bundles (**Fig.**
65 **1a**). Our system consists of a receptor layer, a spinal layer, and a cognitive layer, mimicking the
66 functions of mechanoreceptors, the spinal cord, and the human brain, respectively (**Fig. 1b**). At the
67 receptor layer, iontronic sensing elements are position-encoded with optimized driving frequencies,
68 enabling parallel transmission with ultra-low latency and suppressed crosstalk. At the intermediate
69 spinal layer, sensing signals are decoded, converged, and compressed to minimize the bandwidth
70 consumption for information transmission. At the cognitive layer, large-scale tactile events are
71 received and reconstructed to generate tactile proprioception with high spatiotemporal-resolution for
72 robots. Our skin can be scaled up and integrated into a hierarchical structure, achieving >10,000
73 sensing elements with an 800- μm spatial resolution and a 10.6-ms temporal resolution covering a
74 large-area. Furthermore, we validate the functions of the NI-skin system in a robotic platform (**Fig. 1c-**
75 **e**) to enable the robot to perform challenging tasks such as dynamic grasping of tiny fragile objects
76 and safe self-protection against needles. This work is expected to advance sensing technologies with
77 high spatiotemporal-resolution and large coverage for fine tactile perception with massive sensors

toward human-level robotic perception and manipulation.

Results and discussion

Design and coding principle of the NI-skins

In the hierarchical human sensory system, numerous primary mechanoreceptors are responsible for capturing stimuli and encoding signals ^[22]. Our artificial skin contains highly sensitive and dense iontronic pressure sensors, with each sensor consisting of two electrodes and an overlying soft ionic material. An ionogel containing free cations and anions is synthesized with engineered surface microstructures, and used as the active layer (soft ionic material) of the iontronic pressure sensors (called “iontronic receptors”) (**Fig. 2a**, top left). When an electronic conductor contacts the ionogel, electronic charges in the electrodes and ionic charges in the ionogel accumulate at the interface to form an electric double layer (EDL) ^[28]. The EDL has a nanoscale charge separation ^[29,30] a few orders of magnitude smaller than that in conventional capacitive sensors, thereby generating strong capacitive signals. Such an iontronic sensing mechanism enables miniaturized sensing units with high sensing performances.

Each “neural bundle” in our system integrates a large number of iontronic receptors. To encode spatial positions, each sensing elements is excited with a unique frequency, where the frequency domain encodes location of the iontronic receptor and the amplitude reflects the intensity of the signals (or stimuli). We further developed an all-in-one array assembly to scale up the number of the iontronic receptors while minimizing wiring complexity in the NI-skin. The iontronic skin was fabricated in two steps (**Supplementary Fig. 1**): soft lithography for making the microstructured ionogel film, and integration of the microstructured ionogel film on flexible printed electrodes of coplanar cross matrix via hot pressing. Compared with the trilayer sensor structure (two electrodes sandwiching an ionic

material), this bilayer structure enables high-density fabrication of electrodes through a significantly simplified process (**Supplementary Fig. 2**). The microstructured ionogel is shown in the scanning electron microscopy (SEM) image in **Fig. 2b**, and the electrode array is shown in the optical image in **Fig. 2c**. The electrodes have a center-to-center spacing of 800 μm , corresponding to a receptor density of $\sim 156 \text{ elements cm}^{-2}$, comparable to the density in mechanoreceptors of the human fingertip, where the receptor density is the highest [8,9,25]. This approach supports the prototyping of the NI-skin in diverse sizes, facilitating scalable integration on various robot surfaces (**Supplementary Fig. 3**).

The EDL capacitance of iontronic sensors is affected by ionic kinetics, with the signal magnitude being frequency-dependent [21]. **Figure 2d** shows the capacitance–frequency response of our iontronic receptors as a function of applied pressure. In the initial state (before loading), the electrode-ionogel interface lacks intimate contact, and thus the device is considered as a dielectric capacitor. As the applied pressure increases, the EDL capacitance (C) is markedly enhanced, while the signal magnitude decreases as the excitation frequency rises. In order to eliminate the impact of frequency, the sensitivity of the devices is defined as the frequency-normalized change in capacitance with respect to pressure, expressed as $\delta[(C - C_0)/C_1]/\delta P$, where C_0 is the initial capacitance before loading, C_1 is the EDL capacitance under saturated pressure, particularly 100 kPa in this study, and P is the instantaneous pressure. We show that the corrected response curves of our iontronic receptor are in good consistency under different excitation frequencies. Additionally, the NI-skin receptor offers a limit of detection less than 0.08 g (**Supplementary Fig. 4a**), supporting the robotic fine-grained perception. The receptors can operate stably for over 100,000 loading cycles (**Supplementary Fig. 4b**) that enables long-term durability for robotic sensing.

In the encoding system, orthogonal frequencies enable parallel transmission of multiple signals

within the same frequency band ^[31], allowing interference-free separation through fast Fourier transform (FFT). By discretizing the Fourier transform ^[32], the frequency-bin resolution is expressed as

$$\Delta f_{bin} = \frac{F_s}{N} = \frac{1}{T_s} \quad (1)$$

where F_s is the sampling rate of the analog-to-digital converter (ADC), N is the number of sampling points, and T_s is the total sampling period. As Δf_{bin} decreases (corresponding to an increase in T_s), the main lobe of the spectrum becomes narrower, leading to a higher frequency-resolution and reduced bandwidth occupation, at a cost of longer sampling and increased processing latency. To ensure the accurate separation of orthogonally encoded frequencies, the encoding frequency interval f_{inter} should satisfy:

$$f_{inter} = G \cdot \Delta f_{bin}, G \in \mathbb{Z}_{\geq 1} \quad (2)$$

Therefore, the frequency selection strategy should comprehensively balance spectral efficiency against latency and hardware complexity. Here, the target sampling duration is set to be 10 ms, corresponding to a frequency bin range up to 100 Hz. To minimize spectral leakage and mutual interference, the encoding frequency interval is set to be 200 Hz. Within the neural bundle, 96 neurons are assigned to an encoding frequency band ranging from 1 to 20 kHz (encoding circuit is shown in **Supplementary Fig. 5**). The response of the iontronic elements was measured five times under encoded frequencies (**Fig. 2f**), yielding an average value of 10.07×10^{-3} with a tiny variance of 0.06×10^{-3} . This result ensures consistent responses of the iontronic receptor across different encoding frequencies.

In our neural bundle, the response frequency encodes the spatial location of the devices, while the amplitude reflects the magnitude of stimulus. Mechanical stimulation on different sensing elements

of the NI-skin produced specific encoding frequency responses, with the raw current output varying with pressure (**Fig. 2g-h**). As illustrated in **Fig. 2h**, when a pressure is applied to the iontronic receptors encoded at 4.0, 4.2, and 4.4 kHz, the neural bundle detected the corresponding time-frequency responses and output current pulses with clear feature frequencies. This capability enables parallel signal perception and transmission from a large number of receptors.

Decoding and convergence of large-scale tactile signals

In the human brain, the mechanoreceptors in the lower receptor layer can respond to the touch and transmit large-scale signals to the backend through nerve bundles ^[25,33]. The posterior spinal cord is responsible for signal relay and preliminary processing ^[34], ensuring that aggregated information is efficiently transmitted to the brain for perception while simultaneously enabling rapid initiation of protective reflexes. This neural-hierarchical processing architecture enables large-scale tactile information from the human skin to be perceived and transmitted to the neural system with high spatiotemporal-resolution. Inspired by this, we designed a “spinal layer” to decode sensing signals and perform compression-based preprocessing (**Fig. 3a**) that generates aggregated signals to the “brain” (central processor).

In our signal transmission framework, each neural bundle can be equipped with up to 96 iontronic receptors, encoded by frequency signals ranging from 1 to 20 kHz with a 200 Hz interval. The current signals of the receptors are superimposed and converted through a current-to-voltage converter (C/V converter), followed by acquisition via an ADC (**Supplementary Fig. 6a-b** and **Supplementary Fig. 7**). According to the Nyquist sampling criterion, the ADC sampling rate is set to 50 kHz, which is at least twice the bandwidth of the encoded signal, ensuring alias-free observation for FFT-based decoding. The FFT algorithm is executed on a digital signal processor (DSP) block to reconstruct the

location and intensity information from the frequency-encoded signals (**Supplementary Fig. 6c**). Our method has high accuracy in determining the location of touch, and shows little crosstalk. As shown in **Fig. 3b–d**, when a pressure of 10 kPa is applied to receptors at different locations, the signals output by the C/V converter can be decoded without frequency aliasing. As a result, the adjacent leakage ratio (*ALR*) between encoded frequencies remains below 1%, defined as the ratio of the signal response leaked into adjacent frequency channels to that of the main spectral component.

In our excitation-detection mode, a frequency-encoded voltage is applied to the excitation electrode, and the sensing electrode measures the corresponding current with frequency information, from which the capacitance response at the sensing node can be obtained ^[21] (see **Supplementary Note 1**). With our design, the maximum readout time of the sensory system is approximately 10.6 ms, consisting of a sampling time of 10 ms and a parallel demodulation computation time of ~0.6 ms (**Supplementary Fig. 8**). In the signal transmission chain, this ensures that the NI-skin achieves a 94.3 Hz readout rate that indicates rapid response to dynamic stimuli (**Supplementary Fig. 9**).

Conventional iontronic sensor arrays, which use a piece of shared ionic material, may experience significant crosstalk between sensing units due to ion migration ^[16]. As shown in **Fig. 3e**, the leaked electric field induces the migration of ions, leading to the EDL capacitance at surrounding sensing sites, an undesired crosstalk. In this work, each iontronic sensor is excited and detected at the intersection of array electrodes, where the excitation electrode applies a standardized voltage, and the sensor electrode records the electrical response to obtain its capacitance characteristics. Although using a shared ionogel film, our NI-skin is free of crosstalk. We designed a parallel zero-potential (PZP) at the decoding end, where all sensing electrodes are set to an equivalent zero potential (**Fig. 3f**). This method ensures that the excitation electric field is constrained to the intersection of the excitation and

sensing electrodes, preventing outward divergence. As a result, the EDL capacitance forms exclusively at the intersection node, thereby reducing mutual interference. On the other hand, the PZP mechanism can interrupt the loop current between the parallel components (**Fig. 3g**), effectively suppressing electrical crosstalk within the parallel circuits. Thus, this design achieves a dual effect, effectively mitigating both crosstalk induced by ion migration and parasitic capacitance-related crosstalk within the NI-skin.

Our experimental data show that this method reduces the crosstalk of the NI-skin from $\sim 39.4\%$ to $\sim 1.3\%$, which is even smaller than that of the scheme with isolated ionogel for each sensing unit ($\sim 1.7\%$) (**Fig. 3h**), and thus improving the perceptual precision (**Supplementary Fig. 10**). Furthermore, our method enhances spatiotemporal resolution in recognizing fine structures in patterns and reliably perceives contact contours (**Supplementary Fig. 11, Supplementary Movies 1–3**), which are essential for dexterous manipulation.

A compression block based on three-dimensional discrete wavelet transform (3D-DWT) is implemented in the spinal layer to simplify data transmission (**Supplementary Fig. 12**). The wavelet transform enables highly sparse and compact representations and can be efficiently realized in an edge-computing hardware ^[35]. The 3D-DWT block decomposes the three-dimensional signals into sparse frequency domain coefficients, which are then quantized to reduce the data size. Finally, entropy encoding exploits statistical redundancy to further compress the quantized coefficients. The 3D-DWT-based compression aims to effectively reduce the data transmission size while preserving tactile features with minimal acceptable accuracy loss.

Compressed sensing for large-scale tactile cognition in robotics

209 High spatiotemporal-resolution signals from the large-scale human skin are transmitted to the
210 cerebral cortex layer via a data bus, enabling cognitive analysis and perceptual construction ^[36]. We
211 constructed a robotic sensory system based on the NI-skins, with a hierarchical processing architecture
212 for tactile information transmission, as shown in **Fig. 4a**. Our NI-skins provide large-area coverage on
213 the surface of a robot, and the hierarchical architecture enables rapid processing and transmission of
214 large-scale tactile data.

215 In the hierarchical architecture, the intermediate spinal layer is responsible for aggregating and
216 compressing data, with the compression degree quantified by a compression ratio (CR), defined as the
217 ratio between the size of raw data to that of compressed data. In the 3D-DWT block (**Supplementary**
218 **Fig. 12**), a larger quantization factor Q results in a higher CR at the expense of potential data distortion
219 (**Fig. 4b**).

220 The robot is capable of extracting three-dimensional spatiotemporal features from large-scale
221 sensing signals to perform the recognition and cognition of objects being touched ^[37]. Here, we
222 designed a 3D convolutional neural network (3D-CNN, **Supplementary Fig. 13**) to extract
223 spatiotemporal features from the captured touch signals. As shown in **Fig. 4b**, when the quantization
224 factor Q is set to be greater than 200, the 3D-DWT block significantly sparsifies the tactile information,
225 with a CR exceeding 260. This is because a high Q value effectively removes non-essential details,
226 preserving key structural features. This process can reduce the transmission bandwidth consumption
227 from 13.8 Mbps to 53.3 kbps (**Fig. 4c**). Using the compressed sensing strategy, sparse features allow
228 for inference with a lighter network. Compared with the original neural network (3.95G FLOPS, 80K
229 parameters), the lightweight network requires only 938M FLOPS (23.7% of the original) and 3.6K
230 parameters (4.5% of the original).

Our strategy maximizes the *CR* while retaining essential features. The 3D-CNN extracts spatiotemporal features, with the t-distributed stochastic neighbor embedding (t-SNE) projection illustrating data clustering. The Davies-Bouldin index (DBI) was used to assess cluster separability, with a lower DBI indicating better intra-class compactness and inter-class distinction, validating feature discriminability. We constructed a dataset for grasping 10 object categories (Grasp Dataset, **Fig. 4d** and **Supplementary Fig. 14a**), capturing responses during manipulation. At a *CR* of 260, the clustering quality of 3D-CNN-extracted features slightly decreases (DBI = 1.17), yet recognition accuracy remains above 99.7% (**Fig. 4e**). A dataset (Touch Dataset, **Fig. 4f** and **Supplementary Fig. 14b**) was also created for 10 touch gestures, capturing interactional responses. At a *CR* of 260, 3D-CNN-extracted features remain well-clustered (DBI = 0.89), with a recognition accuracy above 94.2% (**Fig. 4g**). These results demonstrate that our strategy of data compression effectively optimizes transmission bandwidth while ensuring reliable tactile feature extraction by the lightweight network in the central processor.

Manipulation of fine objects

The human skin excels with a vast number of receptors with high spatiotemporal resolution (~ 150 units cm^{-2} and up to 250 Hz) ^[7-9] and small two-point limen (down to 2 mm) ^[25]. Achieving high spatiotemporal resolution tactile perception comparable to that of the human skin remains an ultimate goal of artificial skin. We developed a soft robotic finger omni-directional adaptation embedded with the NI-skin to enable flexible grasping. The NI-skin was able to detect stimuli from sharp objects with a two-point limen of 0.8 mm (**Fig. 5a, b** and **Supplementary Movie 4**), surpassing the smallest two-point limen of the human skin (finger tips). Compared with existing artificial skins ^[5-10,15,16,20,21,27], the NI-skin outperforms in several aspects, such as the number of sensing units ($>10,000$ sensing elements),

253 156 units cm^{-2} spatial resolution, and 94.3 Hz temporal resolution (**Fig. 5c** and **Supplementary Table**
254 **1**).

255 The human hands can dexterously manipulate small and fragile objects, and this requires sensing
256 with high spatial resolution and high sensitivity. Here, a robotic hand with two fingers equipped with
257 our NI-skin can grasp objects as small as 0.5 mm in diameter, exemplified by a thin and fragile pencil
258 lead, because the NI-skin provides exceptional spatial resolution of 800 μm and high sensitivity of
259 10.07 Pa^{-1} . As shown in **Fig. 5d** and **Supplementary Movie 5**, the NI-skin can reliably record real
260 time pressure distribution when the robotic fingers grasp the pencil lead, and the signals during the
261 interaction is recorded in **Fig. 5e**. Utilizing our tactile system, the fingers can delicately manipulate an
262 even thinner object, a soft solder wire with a diameter of 0.2 mm, without inducing any buckling when
263 applying an appropriate load by compressing the wire at both ends (**Supplementary Movie 6**). When
264 buckling of the wire occurs by a human hand, the robotic fingers rapidly adjust their positions so that
265 the wire does not fall off.

266 **Nociceptive sensing and self-protection based on pain-feedback**

267 An important capability of human skin is the feeling harmful pain to trigger rapid self-protection
268 against puncture ^[38-41]. Our tactile system aims to replicate this capability by quickly detecting
269 nociceptive pain at the spinal layer, triggering a protective response. Nociceptive stimuli often come
270 from the interaction with sharp and stiff objects (e.g., needles) that produces high pressure gradient,
271 $\Delta P/\Delta x$, which represents the change in pressure (ΔP) over a certain distance (Δx). The minimum value
272 of Δx is often determined by the two-point limen. Here, our NI-skin has a small two-point limen of
273 800 μm , enabling for the detection of a sufficiently high $\Delta P/\Delta x$ value. Stimuli with varying sharpness
274 levels induce different sensations of pricking on the skin. We thus selected target objects with different

sharpness to stimulate the skin of the finger. The curvature of the objects follows a power law, where the radius of curvature at the edge of the protruding feature can be modified by the body power law exponent n ($0 \leq n \leq 1$, model formula in **Supplementary Note 2** and **Supplementary Fig. 15a**) [38,42]. As shown in **Fig. 5f**, an increasing value of n corresponds to a greater edge curvature, indicating a sharper object, which in turn leads to a smaller response area of the NI-skin during finger grasping. In grasping and releasing cycles, the NI-skin monitored key features such as maximum pressure, activated element count, and maximum pressure gradient (**Fig. 5g**). As n increases, the maximum pressure and pressure gradients increases, while the number of activated elements decreases. These features were used for nociceptive sensing.

We stimulated the NI-skin on the robotic finger with spikes of varying sharpness to quantify the degree of “pain”. We applied stimuli with objects at different n values, recording NI-skin responses to create a pain-perception dataset (**Supplementary Fig. 15b**). A pain prediction model based on Logit regression was developed using three features: maximum pressure, the number of activated sensing units, and the maximum pressure gradient, to assess pain intensity (**Supplementary Note 3, Supplementary Fig. 16**). On the pain-perception dataset, the model achieved a coefficient of determination (R^2) up to 91.1%.

The pain threshold (P_{th}), defined as the critical value output in the pain model that triggers self-protection, is used to prevent further damage to the robot. We show that the robotic hand with its two fingers equipped with the NI-skins performs protective reaction as it manipulates a spiny chestnut (**Supplementary Movie 7** and **Fig. 5h**). In this case, a large number of sensing units are activated. While at least one sensing unit of the NI-skin is subjected to P_{th} , an action to the fingers is trigger to decrease the grasping pressure for the protection of the skin. In another scenario, when the fingers of

the robotic hand touch a needle, only one sensing unit on the skin is activated with a high pressure-gradient exceeding its P_{th} , triggering a protective response (**Supplementary Movie 8**). This case is judged as the needle puncture, and the fingers are thus controlled to withdraw rapidly for preventing further injury of the NI-skin (**Fig. 5i**). Without pain perception, however, the fingers further proceed to the needle, cause damages to a few sensing elements of the NI-skin (**Fig. 5j**).

Discussion

A key goal in human-centered robotics is to achieve human-level perception and manipulation with fine interaction and self-protection. By integrating frequency-encoded receptors, crosstalk suppression, and compressed sensing, our NI-skin mimics the hierarchical processing of the human tactile sensory system, which comprises receptor, spinal, and cognitive layers. Such an architecture enables 800- μm spatial resolution, and the readout of $\sim 10,000$ sensing elements within 10.6 ms without crosstalk. Its ability to manipulate fragile objects and provide real-time nociception demonstrates its potential to enhance robotic dexterity and safety.

This work may provide guideline for the design of next-generation tactile perception architecture suitable for large-scale robotic skins. The current implementation of the encoding-decoding circuitry is relatively bulky, limiting the miniaturization and full integration of the readout interface in artificial skin. Future work should explore integrating the interface circuitry into application-specific integrated circuits (ASICs), with our design serving as an excellent architecture for such ASIC chips.

MATERIALS AND METHODS

Materials

The following chemicals: 3,6-Dioxa-1,8-octanedithiol (D154345), 1,4-Butanediol divinyl ether (B472435), 1,1,1-Tris(3-mercaptopropionyloxymethyl)propane (T464015), 2,2-Dimethoxy-2-phenylacetophenone (B105178), 1-Ethyl-3-methylimidazolium bis(trifluoromethylsulfonyl)imide ([EMIM][TFSI], E101506) were purchased from Aladdin. The thermoplastic polyurethane (TPU) films were purchased from Dongguan Lijin Polyurethane Co., Ltd. The microstructured frosted glass was purchased from Anhui Hengboli Instrument Technology Co., Ltd.

Fabrication of the NI-skin

NI-skin consisted of two components: a microstructured ionogel with a TPU encapsulation layer and an electrode array. These two parts were assembled directly using commercially available double-sided tape. The ionogel precursor was composed of 2.7345 g (15 mmol) of 3,6-Dioxa-1,8-octanedithiol, 2.9862 g (21 mmol) of 1,4-Butanediol divinyl ether, 1.5942 g (4 mmol) of 1,1,1-Tris(3-mercaptopropionyloxymethyl)propane, 0.036 g (0.5 wt% relative to total monomer) of photoinitiator 2,2-Dimethoxy-2-phenylacetophenone, and 0.5852 g (8 wt% relative to total monomer) of 1-Ethyl-3-methylimidazolium bis(trifluoromethylsulfonyl)imide. All components were thoroughly mixed and oscillated until a clear homogeneous solution was obtained. The electrode array was manufactured using flexible printed circuit (FPC) processing technology and was outsourced to Shenzhen Jialichuang Technology Group Co., Ltd.

Characterization of sensing properties of sensing elements

An inductance-capacitance-resistance meter (E4980AL, KEYSIGHT) was initially used to measure the capacitance of the sensors. Capacitance measurements were all performed at 100 mV and in the

338 frequency range from 100 Hz to 100 kHz. The 3D-printed indenters were used to apply the
339 displacement loads. The pressure applied to the sensors was controlled and recorded by a tensiometer
340 machine (LD23.501, LSD). A lock-in amplifier (MFLI, Zurich Instruments) was used for aliasing
341 signal acquisition and spectrum analysis.

342 **Development of interface circuitry for NI-skin**

343 The direct digital frequency synthesizers (DDS, AD9833, Analog Devices Instruments) were used to
344 generate frequency-tunable AC excitation signals. The backend circuit consisted of a high-pass filter
345 with a cutoff frequency of 200 Hz and a voltage follower implemented using an operational amplifier
346 (OPA4388, Texas Instruments). The design of the decoding circuit and computation block are shown
347 in **Supplementary Fig. 7**. The C/V converters were implemented with a precision operational
348 amplifier (OPA4388, Texas Instruments), in which the reference resistor was implemented using a
349 programmable digital potentiometer (TPL0501-100) to enable adaptive adjustment of the output
350 conversion voltage. The 16-bit analog-to-digital converters (ADC, AD7606, Analog Devices
351 Instruments) were employed to acquire voltage signals from the analog front-end. Each ADC chip
352 provides eight synchronous voltage-sampling channels. The sampling rate was set at 50 kSPS, and the
353 data were read out via a parallel SPI bus. An FPGA (Altera EP4CE6F17C8N) was deployed for parallel
354 acquisition from multiple ADCs and subsequent parallel FFT demodulation. The FPGA processes
355 multi-channel ADC parallel sampling and performs parallel FFT demodulation using DSP blocks to
356 extract the frequency-encoded sensory response. The demodulated signals are then aggregated and
357 compressed. The compressed data is transmitted to the central processor via USB or Ethernet as the
358 main data bus.

Demonstration setup

For the tactile perception task of dexterous grasping, an NI-skin (48×48 elements in $7\text{cm} \times 7\text{cm}$) was mounted on a commercial dexterous hand (RH56BFX) to record sensing signals when grasping various everyday objects. For the large-area tactile sensing task on a robotic body, an NI-skin (96×96 elements in $15\text{ cm} \times 15\text{ cm}$) was attached to the outer surface of a humanoid robot model to perceive and record tactile responses under different contact objects and gestures. For the fingertip fine-perception and nociception tasks, a high-density NI-skin ($156\text{ elements cm}^{-2}$) was mounted on the soft finger of a robotic gripper ^[43,44], which was installed on a commercial robotic arm (Universal Robot 10e). Tactile signals were transmitted via a data bus using the USB/TCP protocol to a laptop computer serving as the central processor, which in turn controlled the robotic arm (or gripper) motion through TCP/IP communication. The interactive user software for the host computer was developed using Python 3.9 with the PyQt5, PyQtGraph, and OpenCV frameworks. It supported real-time data transmission, waveform visualization, graphical rendering, tactile map visualization, and data storage.

Construction of dataset

Grasping Dataset: this dataset recorded tactile pressure data from the robotic hand's NI-skin during the grasping of 10 object categories, with each object grasped 4 times. Data was collected at 94 Hz, with a grasp duration of 3-5 s, covering tactile responses from 10 daily items (**Fig. 4c**). Touch Dataset: This dataset captured dynamic pressure data from 10 different touch gestures applied to the large-area NI-skin on the robotic body. Each gesture lasted 3-10 s and was performed by four subjects, with data being recorded at 94 Hz. Pain-perception Dataset: This dataset recorded tactile responses from the NI-skins on robotic fingers under 5 different sharpness levels (controlled by a power-law index), defined

380 as varying pain degree (0-100%, **Supplementary Fig. 15**). Data was collected at 94 Hz under a
381 constant force of ~500 mN, with each pain level being recorded for 3-5 seconds.

References

1. Radosavovic, I. et al. Real-world humanoid locomotion with reinforcement learning. *Sci. Rob.* **9**, eadi9579 (2024).
2. Barreiros, J.A. et al. Learning contact-rich whole-body manipulation with example-guided reinforcement learning. *Sci. Rob.* **10**, eads6790 (2025).
3. Kennedy III, M. The role of collaborative robotics in assistive and rehabilitation applications. *Sci. Rob.* **8**, eadk6743 (2023).
4. Billard, A.G. Robots that share our spaces require proprioception and a sense of touch. *Science* **389**, eaea2492 (2025).
5. Corniani, G. & Saal, H.P. Tactile innervation densities across the whole body. *Journal of Neurophysiology* **124**, 1229-1240 (2020).
6. Deflorio, D., Di Luca, M. & Wing, A.M. Skin and mechanoreceptor contribution to tactile input for perception: a review of simulation models. *Front. Hum. Neurosci.* **16**, 862344 (2022).
7. Weber, A.I. et al. Spatial and temporal codes mediate the tactile perception of natural textures. *Proc. Natl. Acad. Sci. U.S.A.* **110**, 17107-17112 (2013).
8. Johansson, R.S. & Flanagan, J.R. Coding and use of tactile signals from the fingertips in object manipulation tasks. *Nat. Rev. Neurosci.* **10**, 345-359 (2009).
9. Kim, T. et al. Dynamic tactility by position-encoded spike spectrum. *Sci. Rob.* **7**, eabl5761 (2022).
10. Oh, H., Yi, G.-C., Yip, M. & Dayeh, S.A. Scalable tactile sensor arrays on flexible substrates with high spatiotemporal resolution enabling slip and grip for closed-loop robotics. *Sci. Adv.* **6**, eabd7795 (2020).
11. Yan, Y. et al. Soft magnetic skin for super-resolution tactile sensing with force self-decoupling. *Sci. Rob.* **6**, eabc8801 (2021).
12. Kong, D. et al. Super-resolution tactile sensor arrays with sparse units enabled by deep learning. *Sci. Adv.* **11**, eadv2124 (2025).
13. Hardman, D., Thuruthel, T.G. & Iida, F. Multimodal information structuring with single-layer soft skins and high-density electrical impedance tomography. *Sci. Rob.* **10**, eadq2303 (2025).
14. Liu, Z. et al. A three-dimensionally architected electronic skin mimicking human mechanosensation. *Science* **384**, 987-994 (2024).
15. Sundaram, S. et al. Learning the signatures of the human grasp using a scalable tactile glove. *Nature* **569**, 698-702 (2019).

- 413 16. Shi, J. et al. Embedment of sensing elements for robust, highly sensitive, and cross-talk-free
414 iontronic skins for robotics applications. *Sci. Adv.* **9**, eadf8831 (2023).
- 415 17. Luo, Y. et al. Learning human–environment interactions using conformal tactile textiles. *Nat.*
416 *Electron.* **4**, 193-201 (2021).
- 417 18. Mei, S. et al. High-density, highly sensitive sensor array of spiky carbon nanospheres for strain
418 field mapping. *Nat. Commun.* **15**, 3752 (2024).
- 419 19. Chen, Y. et al. Capacitive in-sensor tactile computing. *Nat. Commun.* **16**, 5691 (2025).
- 420 20. Lee, W.W. et al. A neuro-inspired artificial peripheral nervous system for scalable electronic skins.
421 *Sci. Rob.* **4**, eaax2198 (2019).
- 422 21. Li, Z. et al. Ultrafast readout, crosstalk suppression iontronic array enabled by frequency-coding
423 architecture. *npj Flexible Electron.* **8**, 9 (2024).
- 424 22. Abraira, V.E. & Ginty, D.D. The sensory neurons of touch. *neuron* **79**, 618-639 (2013).
- 425 23. Wang, W. et al. Neuromorphic sensorimotor loop embodied by monolithically integrated, low-
426 voltage, soft e-skin. *Science* **380**, 735-742 (2023).
- 427 24. Chen, L. et al. Spike timing–based coding in neuromimetic tactile system enables dynamic object
428 classification. *Science* **384**, 660-665 (2024).
- 429 25. Liu, F. et al. Neuro-inspired electronic skin for robots. *Sci. Rob.* **7**, eabl7344 (2022).
- 430 26. Gao, Y. et al. A neuromorphic robotic electronic skin with active pain and injury perception. *Proc.*
431 *Natl. Acad. Sci. U.S.A.* **122**, e2520922122 (2025).
- 432 27. Long, Z. et al. One-wire reconfigurable and damage-tolerant sensor matrix inspired by the auditory
433 tonotopy. *Sci. Adv.* **9**, eadi6633 (2023).
- 434 28. He, Y., Cheng, Y., Yang, C. & Guo, C.F. Creep-free polyelectrolyte elastomer for drift-free
435 iontronic sensing. *Nat. Mater.* **23**, 1107-1114 (2024).
- 436 29. Yuan, Y.m. et al. Microstructured polyelectrolyte elastomer-based iontronic sensors with high
437 sensitivities and excellent stability for artificial skins. *Adv. Mater.* **36**, 2310429 (2024).
- 438 30. Bai, N. et al. Graded intrafillable architecture-based iontronic pressure sensor with ultra-broad-
439 range high sensitivity. *Nat. Commun.* **11**, 209 (2020).
- 440 31. Hernando, J.L. & Armada, A.G. Frequency-modulated OFDM: A new waveform for high-mobility
441 wireless communications. *IEEE Trans. Commun.* **71**, 540-552 (2022).

32. Hama, Y. &Ochiai, H. On the achievable spectral efficiency of non-orthogonal frequency division multiplexing. *IEEE Trans. Commun.* **71**, 6246-6257 (2023).
33. Delmas, P., Hao, J. &Rodat-Despoix, L. Molecular mechanisms of mechanotransduction in mammalian sensory neurons. *Nat. Rev. Neurosci.* **12**, 139-153 (2011).
34. Peirs, C. &Seal, R.P. Neural circuits for pain: recent advances and current views. *Science* **354**, 578-584 (2016).
35. Slepyan, A., Zakariaie, M., Tran, T. &Thakor, N. Wavelet transforms significantly sparsify and compress tactile interactions. *Sensors* **24**, 4243 (2024).
36. Sobinov, A.R. &Bensmaia, S.J. The neural mechanisms of manual dexterity. *Nat. Rev. Neurosci.* **22**, 741-757 (2021).
37. Li, Y.-K., Meng, Q.-H., Yang, T.-H., Wang, Y.-X. &Hou, H.-R. Touch gesture and emotion recognition using decomposed spatiotemporal convolutions. *IEEE Trans. Instrum. Meas.* **71**, 1-9 (2022).
38. Osborn, L.E. et al. Prosthesis with neuromorphic multilayered e-dermis perceives touch and pain. *Sci. Rob.* **3**, eaat3818 (2018).
39. Lee, G.I. &Neumeister, M.W. Pain: pathways and physiology. *Clinics in plastic surgery* **47**, 173-180 (2020).
40. Yam, M.F. et al. General pathways of pain sensation and the major neurotransmitters involved in pain regulation. *Int. J. Mol. Sci.* **19**, 2164 (2018).
41. Liu, F. et al. Printed synaptic transistor-based electronic skin for robots to feel and learn. *Sci. Rob.* **7**, eabl7286 (2022).
42. Santos, W.F. &Lewis, M.J. Aerothermodynamic performance analysis of hypersonic flow on power law leading edges. *Journal of Spacecraft and Rockets* **42**, 588-597 (2005).
43. Liu, X., Han, X., Hong, W., Wan, F. &Song, C. Proprioceptive learning with soft polyhedral networks. *The International Journal of Robotics Research* **43**, 1916-1935 (2024).
44. Wu, T. et al. MagiClaw: A Dual-Use, Vision-Based Soft Gripper for Bridging the Human Demonstration to Robotic Deployment Gap. *arXiv preprint arXiv:2509.19169* (2025).

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488

489 **Competing interest:** Authors declare that they have no competing interests.

490

491 **Data availability:** All data required to support the conclusions of this study are provided within the
492 main text and Supplementary Materials. Additionally, all relevant code is publicly accessible at
493 <https://github.com/jioy/NI-skins.git>.

494

495 **Supplementary Materials**

496 **The PDF file includes:**

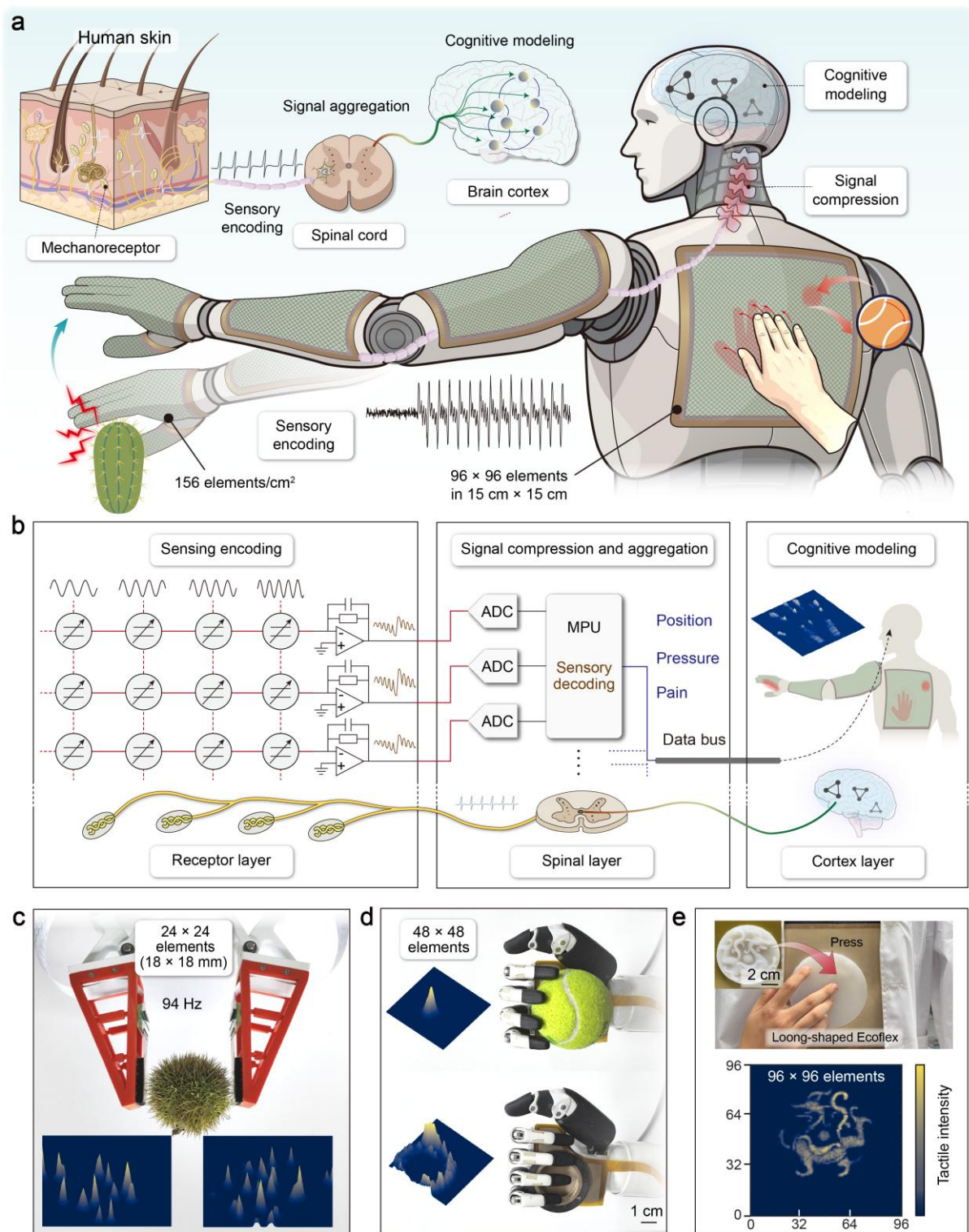
497 Supplementary Notes 1 to 3

498 Supplementary Figures 1 to 16

499 Supplementary Table 1

500 **Other Supplementary Material for this manuscript includes the following:**

501 Supplementary Movies 1 to 8



503

504 **Fig. 1. NI-skin system mimicking the hierarchical architecture of the human tactile sensory**
505 **system. (a)** Overview of the NI-skin system with 10k sensing units and a neural-hierarchical
506 **processing architecture. (b)** A three-layer hierarchical design containing a receptor layer, a spinal layer,
507 **and a cerebral cortex layer. (c)** Sensing signals of NI-skins during the grasp of sharp objects of a gripper.
508 **(d)** Signal mapping of a robotic hand equipped with a 48×48 array during dexterous grasping of
509 **different objects. (e)** High spatial-resolution sensing in large-area robotic coverage with a 96×96 array.

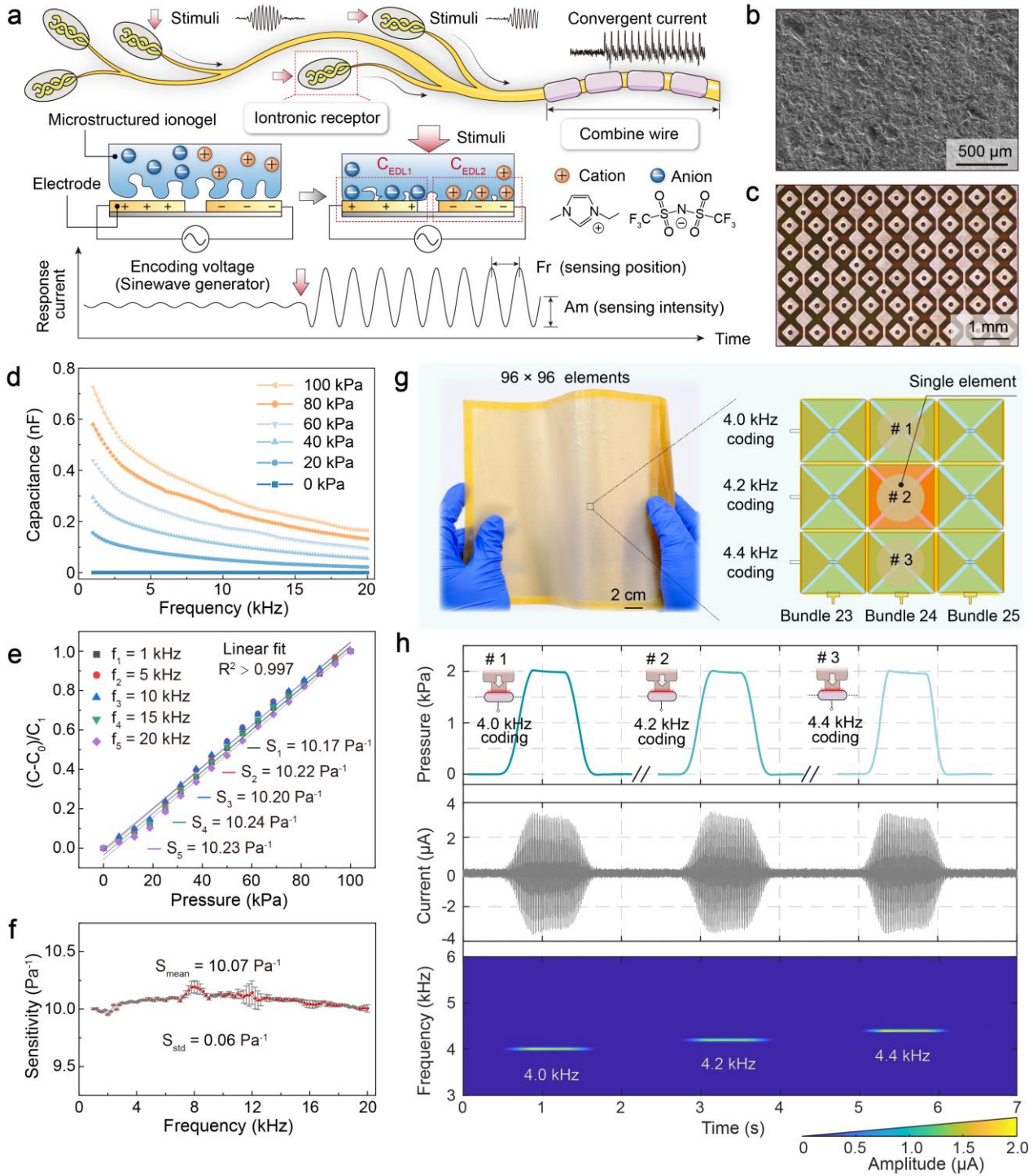


Fig. 2. Design and coding principle of the NI-skin system. (a) Schematic illustration of the structure and sensing principle of iontronic receptors. (b) Scanning electron microscopy (SEM) image of the microstructure on ionogel surface. (c) Optical image of the electrode array. (d) Capacitance response versus excitation frequency under varying applied pressures. (e) Normalized response curve at different excitation frequencies. (f) Consistency of sensitivity of a sensing unit across excitation frequencies from 1 to 20 kHz. (g) Photograph of the large-scale 96×96 NI-skin and schematic illustration of the frequency-encoded signals used for spatial localization at the receiver. (h) Time-frequency analysis of encoded signal response under constant force applied at different positions.

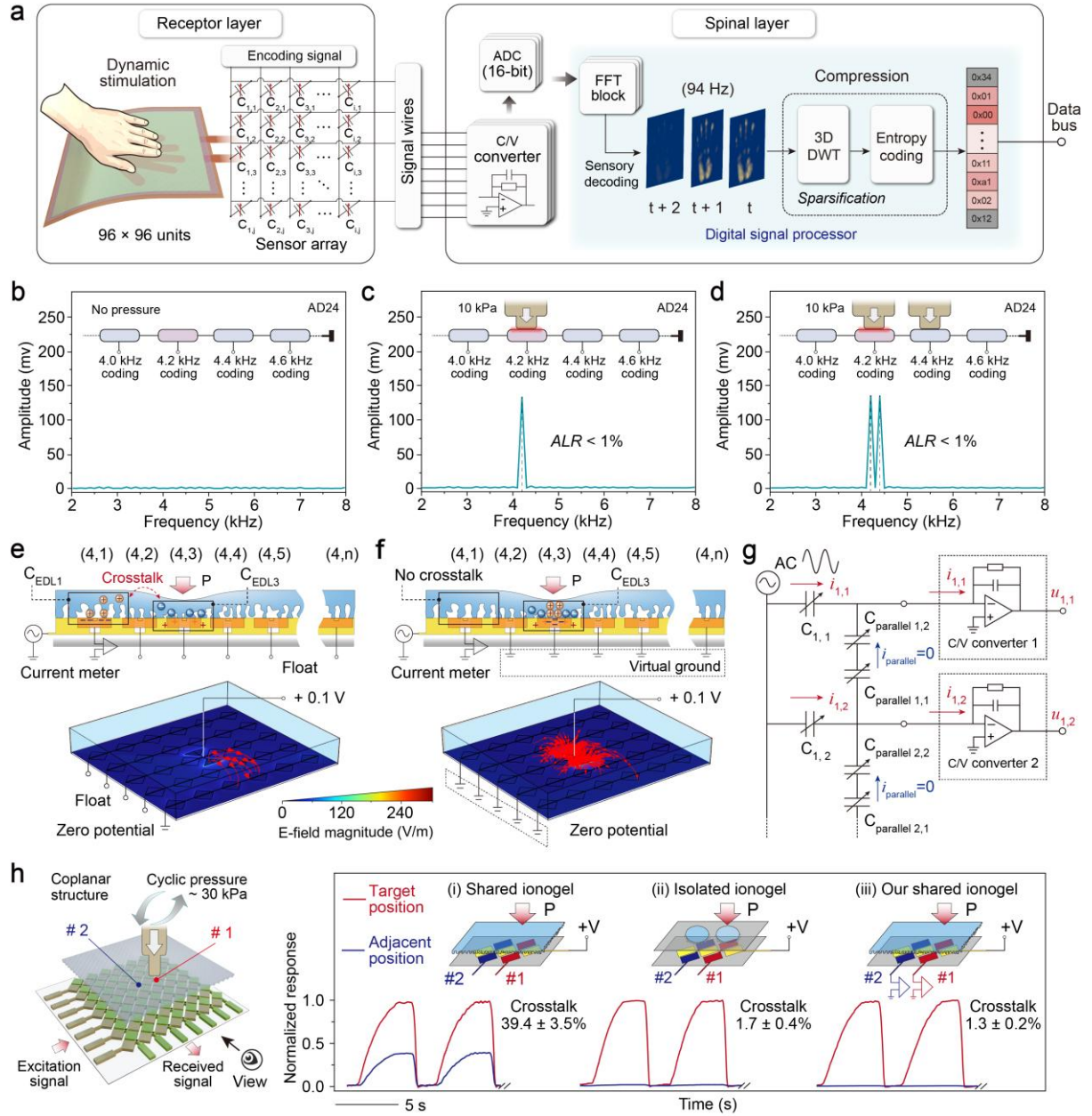


Fig. 3. Decoding and convergence of large-scale tactile signals. (a) Flowchart of decoding and compressed convergence for sensory encoding signals. The spinal layer is responsible for decoding encoded signals from receptors, subsequently compressing and aggregating the signals onto a data bus for the transmission to the central processor. (b-d) Response of decoded signals under pressure stimuli at different locations. *ALR* quantifies the extent to which the energy of the main spectral peak leaks into adjacent frequency bins. (e) Schematic illustration and simulation of ion-migration-induced crosstalk under electrode floating connection. (f) Schematic illustration and simulation of ion-migration-induced crosstalk suppression in the NI-skin decoding system equipped with the PZP mechanism. (g) Schematic illustration of electrical crosstalk suppression between parallel circuit elements in the array under the PZP mechanism. (h) Crosstalk suppression analysis between iontronic sensing elements. (i) Without crosstalk suppression, the crosstalk reaches up to ~39.4%. (ii) Under ionogel separation, crosstalk can be reduced to be ~1.7%. (iii) With our PZP design, crosstalk is reduced to ~1.3%.

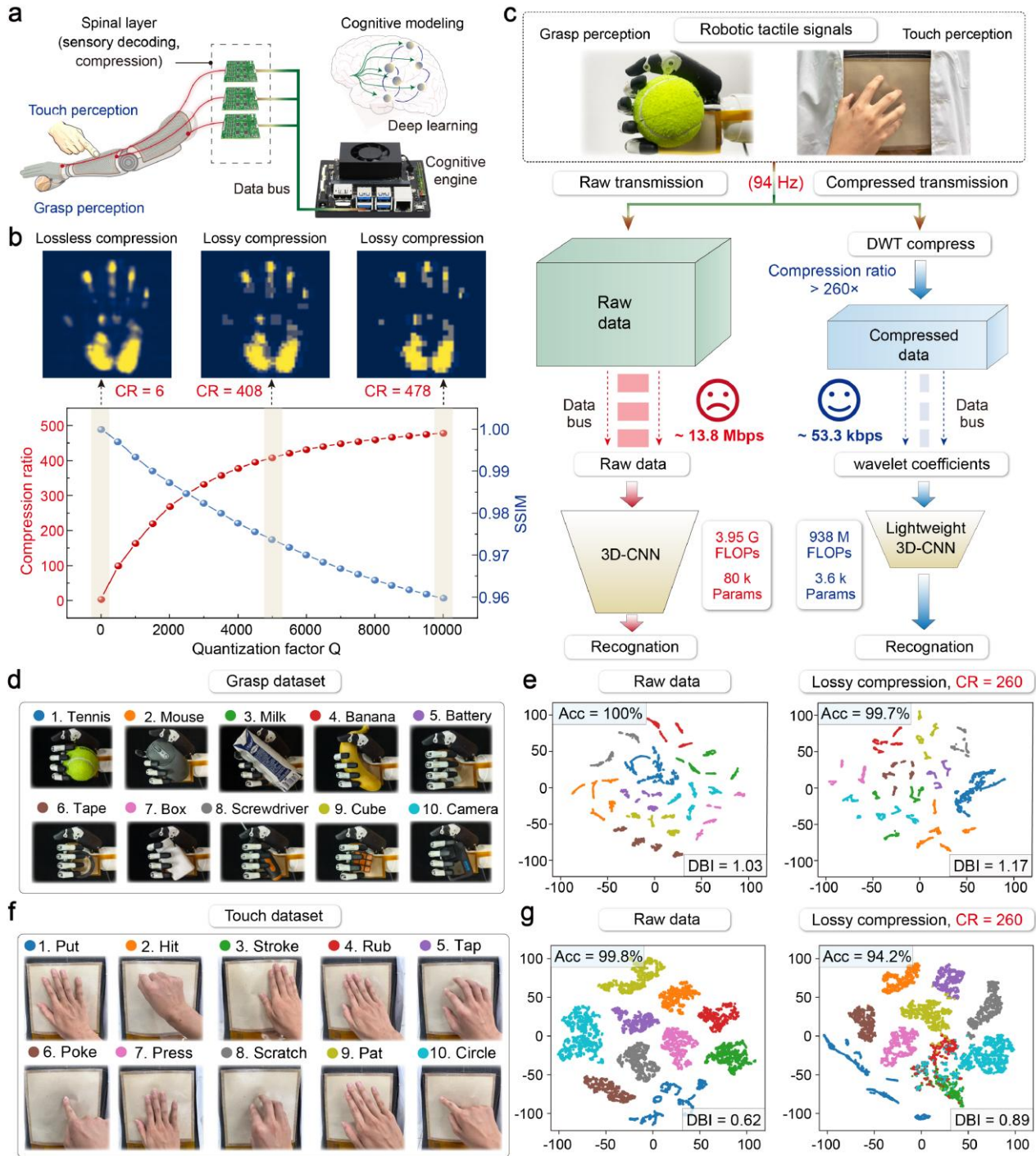


Fig. 4. Compressed sensing for large-scale tactile cognition in robotics. (a) Hardware framework of the hierarchical processing architecture for the aggregation and transmission of large-scale tactile information. (b) Trade-off between compression ratio and structural similarity index (SSIM) for optimizing lossy compression performance. (c) Demonstration of the advantages of tactile compression in reducing transmission bandwidth and enabling lightweight inference. (d) Dataset of grasping 10 different objects. (e) t-SNE visualization of the grasp dataset shows clustering of raw and compressed tactile events, indicating that key palmar tactile features are retained at high compression ratios. (f) Dataset of 10 distinct touch actions. (g) t-SNE visualization of the touch dataset reveals clustering of raw and compressed tactile events, demonstrating that key somatosensory features are preserved even at high compression ratios.

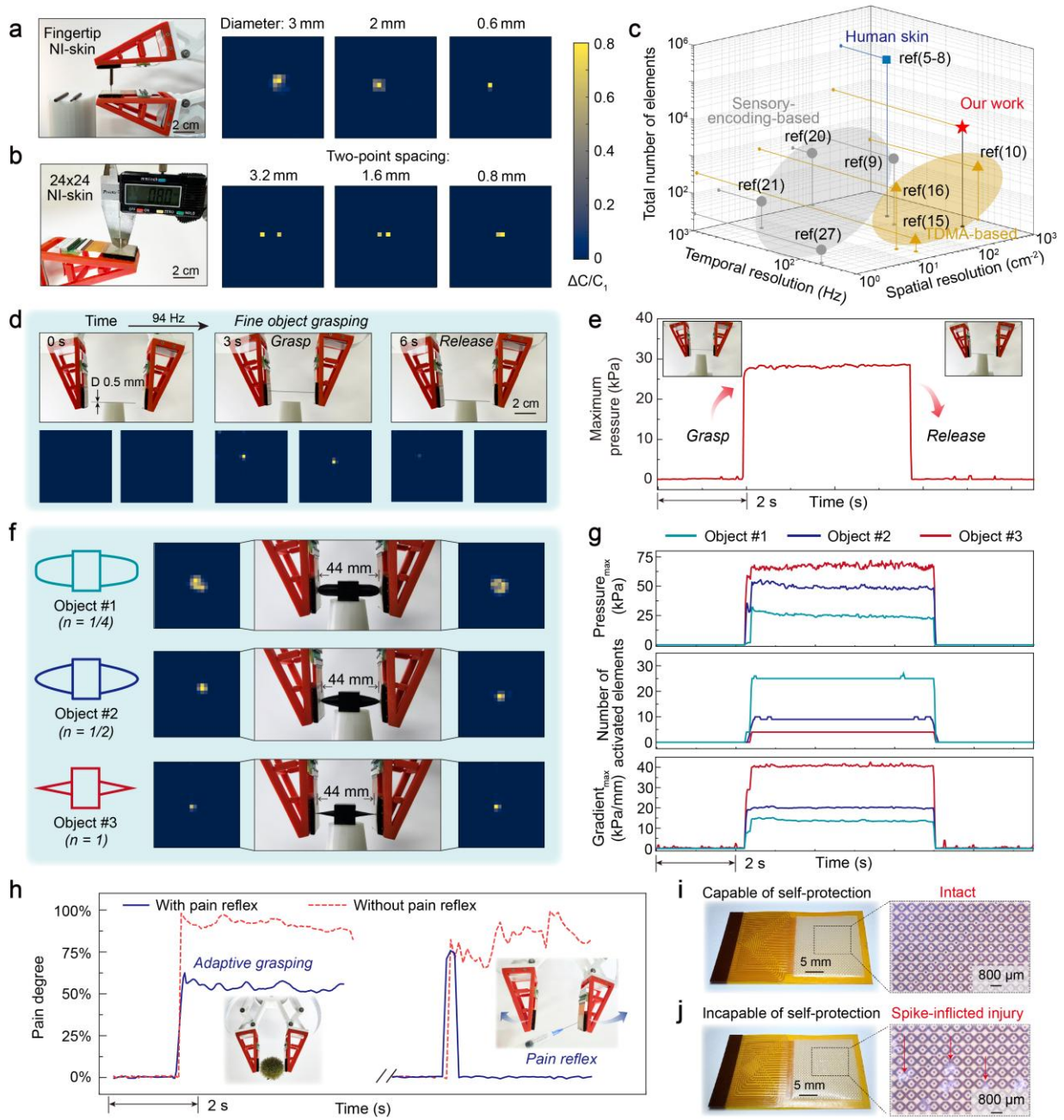


Fig. 5. Robotic fine manipulation and self-protection enabled by high spatiotemporal-resolution tactile perception. (a) Spatially resolving of fine structures with different diameters (3, 2, and 0.6 mm) using the NI-skin. (b) Determination of the two-point limen, which is about 0.8 mm. (c) Comparison of our NI-skin with human skin [5-8] and reported artificial skins [9,10,15,16,20,21,27] in terms of temporal resolution, spatial resolution, and the number of sensing elements. (d) Demonstration of a robotic hand equipped with NI-skin grasping a 0.5-mm diameter pencil lead. Demonstration of a robotic finger equipped with NI-skin grasping a 0.5-mm pencil lead, showing the real-time pressure distribution. (e) Real-time response curve of the maximum pressure on the NI-skin during a robotic finger grasping the pencil lead. (f) Tactile response distribution of high-density NI-SKIN during robotic finger grasping of objects with varying sharpness, modulated by the power-law index n (#1-#3). (g) Tactile feature responses of high-density NI-SKIN during robotic finger grasping of objects with varying sharpness, including maximum pressure, activated element count, and maximum pressure gradient. (h)

558 Demonstration of safe interaction and self-protection with a robotic finger equipped with high
559 spatiotemporal-resolution tactile perception. **(i)** Effectiveness of robotic self-protection with tactile
560 pain perception. **(j)** Mechanical injury caused by the absence of pain perception and timely avoidance
561 in robots.
562

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