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# An Intelligent Robotic System Capable of Sensing and Describing Objects Based on Bimodal, Self-Powered Flexible Sensors

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This study presents an intelligent soft robotic system capable of perceiving, describing, and sorting objects based on their physical properties. This work introduces a bimodal self-powered flexible sensor (BSFS) based on the triboelectric nanogenerator and giant magnetoelastic effect. The BSFS features a simplified structure comprising a magnetoelastic conductive film and a packaged liquid metal coil. The BSFS can precisely detect and distinguish touchless and tactile models, with a response time of 10 ms. By seamlessly integrating the BSFSs into the soft fingers, this study realizes an anthropomorphic soft robotic hand with remarkable multimodal perception capabilities. The touchless signals provide valuable insights into object shape and material composition, while the tactile signals offer precise information regarding surface roughness. Utilizing a convolutional neural network (CNN), this study integrates all sensing information, resulting in an intelligent soft robotic system that accurately describes objects based on their physical properties, including materials, surface roughness, and shapes, with an accuracy rate of up to 97%. This study may lay a robotic foundation for the hardware of the general artificial intelligence with capacities to interpret and interact with the physical world, which also serves as an interface between artificial intelligence and soft robots.

1. Introduction

Soft robots possess inherent flexibility and safety features and are promising for various practical applications.<sup>[1-6]</sup> Numerous flexible sensors have been developed based piezoelectric,<sup>[7,8]</sup> piezoresistive,<sup>[9–12]</sup> on capacitive,<sup>[13-15]</sup> triboelectric,<sup>[16,17]</sup> and giant magnetoelastic effects to endow the soft robots with sensing abilities.[18,19] While these sensors enable soft robots to perceive specific types of information, their single-mode character fails to satisfy the requirements for comprehensive intelligent behaviors of soft robots. In particular, soft robots, such as soft robotic hands, necessitate multimodal information perception and description capabilities akin to human hands (Figure 1).<sup>[20,21]</sup> To broaden the scope of practical applications of soft robots, developing high-performance multimodal flexible sensors and intelligent soft robotic systems integrating machine learning is imperative.

Until now, many efforts have been made

to develop multimodal flexible sensors. There are two main categories. The first category involves fabricating sensors with single-functional materials.<sup>[22–31]</sup> For instance, liquid metal can be encapsulated within a silicone rubber channel to enable pressure and bending perception.<sup>[23]</sup> Flexible capacitive sensors, comprising suitable materials, can detect pressure and the distance to external objects.<sup>[24]</sup> However, challenges remain in separating and decoupling signals of each stimulus type.

The second category focuses on diversifying the range of functional materials and employing a single transition mechanism for each material to achieve multimodal sensing.<sup>[32–41]</sup> For instance, Liu et al. developed a flexible multimodal sensor using liquid metal and triboelectric nanogenerators to enable distance and pressure sensing.<sup>[41]</sup> Kim et al. fabricated a complex multimodal sensor utilizing an ionic liquid, soft optical components, and conductive fabric to perceive stretching, bending, and compression.<sup>[36]</sup> Although these sensors successfully disentangle combined multimodal information, they often have intricate structural issues and are complex to fabricate. Furthermore, most

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Figure 1. The intelligent soft robotic system perceives, describes, and sorts objects by their physical properties.

existing flexible multimodal sensors exhibit slow response and require external sources to power themselves.

Researchers have endeavored to develop intelligent soft robots with flexible multimodal sensors to perceive diverse environmental information and enable real-life applications.<sup>[42-46]</sup> For instance, Zhao et al. embedded flexible optical fibers within a soft robotic hand to detect strain and facilitate texture or shape perception.<sup>[43]</sup> Hao et al. utilized liquid metal sensors attached to the gripper's surface to perceive object shapes.<sup>[45]</sup> With their broad material selection and high output, triboelectric nanogenerators hold significant promise for integration with soft robotic hands.<sup>[47-52]</sup> Jin et al. embedded triboelectric bending and tactile sensors on a soft robotic hand's top and bottom surfaces to enable object identification through shape perception.<sup>[47]</sup> However, the current intelligent soft robotic hands lack comprehensive multimodal information perception and description capabilities. These limitations hinder the ability of soft robotic hands to perceive multimodal environmental information and perform delicate manipulation tasks.

In practical applications, the current main approaches for robots to touchless perceive the external environment relies on vision.<sup>[53–56]</sup> Nevertheless, the vision method faces challenges in sensing and describing the objects' material properties and surface roughness. Therefore, integrating a soft robot capable of multimodal sensing and then describing objects becomes a valuable complement to the current robot perception. Soft robots that can describe objects' physical characteristics with multiple physical factors would enhance the robots' interaction and operational abilities with the real world.

In this study, we propose an intelligent perception and recognition soft robotic system that addresses these challenges by incorporating a bimodal self-powered flexible sensor (BSFS). Leveraging the principles of triboelectric nanogenerators and the giant magnetoelastic effect, the BSFS demonstrates exceptional sensitivity and clear discrimination between touchless and tactile modes, with a response time of 10 ms. By seamlessly integrating the BSFSs into the soft fingers, we realize an anthropomorphic soft robotic hand with remarkable multimodal perception capabilities. The touchless signals provide valuable insights into object shape and material composition, while the tactile signals offer precise information regarding surface roughness. Using a convolutional neural network (CNN), we implemented an intelligent soft robotic system to perceive, describe, and sort objects based on their physical properties.

#### 2. Results and Discussion

#### 2.1. Working Principle and Sensing Performance of BSFS

As shown in Figure 2a, the BSFS comprises a magnetoelastic conductive film and a packaged liquid metal coil. The fabrication process is shown in Figure S1 (Supporting Information). We doped the micromagnets (Figure S2, Supporting Information) and carbon nanotubes (Figure S3, Supporting Information) into the silicone rubber material to implement the magnetoelastic conductive film. Then we blend the film to induce the air microbubbles, resulting in a porous structure on the film surface. The cross-section of the magnetoelastic conductive film is shown in Figure 2b. The porous structure can facilitate a reduction in mechanical modulus and an improvement in mechanicalto-magnetic energy conversion. Subsequently, the magnetoelastic conductive film is magnetized using a magnetizer (WD-80, Yingpu), causing reorientation and movement of the micromagnets, finally forming a wavy magnetic chain. The liquid metal layer has 22 turns of coils, which were printed and then encapsulated with silicone rubber (Figure S4, Supporting Information).

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**Figure 2.** Structure and working mechanism of the proposed bimodal self-powered flexible sensor (BSFS). a) The BSFS consists of two functional, flexible films, a magnetoelastic conductive film, and a liquid metal coil with package film. b) The scanning electron microscopy image of the magnetoelastic conductive film's cross-section. Scale bar: 200  $\mu$ m. c) Photograph of the BSFS in a bending state. Scale bar: 5 mm. d) Hysteresis loop of the soft magnetoelastic conductive film. Magnetic flux density mappings of the soft magnetoelastic film in the initial state e) and a compressed state f). g) The



The flexibility and deformability of the overall structure of the BSFS is shown in Figure 2c, because all components are made of flexible materials.

Notably, the magnetoelastic conductive film exhibits notable magnetoelasticity, characterized by a remnant magnetization of up to 321.7 emu/g, as shown in Figure 2d. We established a dedicated platform to measure the magnetic flux density mappings on the surface under different uniaxial stresses (0 and 256 kPa) (Figure S5, Supporting Information). The results showed a substantial decrease in the magnetic flux density of a  $3 \times 3 \times 0.3$  cm magnetoelastic conductive film, amounting to 16.9%, as depicted in Figure 2e,f. Notably, our system's relative magnetic flux density decreases surpassed that of traditional magnetoelastic systems by two orders of magnitude. We conducted an experiment to compare the performances between porous and non-porous magnetoelastic conductive films. In particular, we measured the surface magnetic field intensity of both types of films before and after applying the same pressure and calculated the variation in surface magnetic field intensity. As shown in Figure S6 (Supporting Information), the porous magnetoelastic conductive film exhibited a notably higher surface magnetic field variation than the nonporous magnetoelastic conductive film. This experimental result shows that a porous structure can enhance the performance of the magnetoelastic conductive film in terms of mechanical-tomagnetic energy conversion.

The comprehensive touchless and tactile perception principle of the BSFS is illustrated in Figure 2g. During the initial stage (i), the external object obtains negative charges based on the triboelectrification effect after repeated contact. Due to the distance from the external object, the magnetoelastic conductive film acquires minimal positive charges. In stage (ii), as the external object approaches the magnetoelastic conductive film, the electric potential between the film and the ground changes based on the electrostatic induction effect. This change drives free electrons to flow from the magnetoelastic conductive film to the ground, generating a circuit current. In stage (iii), the BSFS begins to deform due to contact pressure from the external object acting on the magnetoelastic conductive film. With the external object approaching the magnetoelastic conductive film, more free electrons flow to the ground, generating a current in the same direction. Simultaneously, the micromagnet chain structure changes as the magnetoelastic conductive film deforms under contact pressure, weakening the surface magnetic flux density. Based on the principle of electromagnetic induction, the liquid metal coil generates a current corresponding to the magnetic field variation. In stage (iv), the distance is minimized when the external object is in full contact with the BSFS, and the free electrons stop moving between the ground and the magnetoelastic conductive film. As a result, no current is generated in the liquid metal coil as the surface magnetic flux density reaches its minimum. In stage (v), with the release of the external pressure, the free electrons flow back from the ground to the magnetoelastic conductive film, generating a current in the opposite direction.

Similarly, a reverse current is induced in the liquid metal coil as the micromagnet wavy chain structure recovers, causing the magnetic flux density to return to its initial state. In stage (vi), as the external object separates from the BSFS, the number of electrons flowing back to the magnetoelastic conductive film increases, generating a current in the same direction as the previous state. Finally, an electrical equilibrium is established when the external object moves away from the BSFS. In addition, the BSFS enables self-powered sensing by harnessing the principles of the triboelectric nanogenerator and giant magnetoelastic effect.

We established a testing platform (Figure S7, Supporting Information) to characterize the performance of the BSFS. The external object was attached to the end of a linear motor (E1100, LinMot), while the BSFS was fixed on the top of a commercial high-precision sensor (mini40, ATI Industrial Automation). The touchless signal output  $\Delta U$  and the tactile signal output  $\Delta I$ were measured by electrometers (Keithley 6514, Tektronix Inc.). Figure 3a illustrates the BSFS output signals dependent on the distance between the BSFS and external object. As the distance increases, the output signal  $\Delta U$  gradually decreases from 22.56 to 0 V, while the tactile signal  $\Delta I$  stabilizes near 0. This observation indicates that the distance can modulate the touchless signal output. However, it does not affect the tactile signal output, enabling the BSFS to decouple touchless and tactile sensing models. Figure 3b demonstrates the capability of BSFS to perceive pressure. As the pressure acting on the BSFS increases from 2 to 30 kPa, the touchless output signal  $\Delta U$  initially increases rapidly and then gradually rises to a maximum value of 8.2 V. The tactile signal increases linearly to 3.4 µA, facilitating the detection of contact pressure by the BSFS.

Furthermore, different materials of the external objects possess distinct electron affinities, which can influence triboelectrification and electrostatic induction, subsequently altering the touchless output signal of the BSFS. Based on the principle of electromagnetic induction, the tactile sensing signal will not be affected by the material properties. We measured signal outputs under the same test conditions on seven different materials, as shown in Figure 3c. The touchless signal differed among these materials, while the tactile signal remained almost unchanged.

To assess the dynamic response of the BSFS, we performed rapid approaching and pressing tests, as depicted in Figure 3d,e. The touchless signal exhibits negligible dynamic response time owing to the active sensing principle, and the dynamic response time of the tactile signal is less than 10 ms. This rapid-dynamic response capability empowers the BSFS to detect more comprehensive information and broadens its potential application

working mechanism of the BSFS: i) The external object (aqua) obtains negative charges after several contacts due to the triboelectrification effect. ii) When an external object approaches the magnetoelastic conductive film (indicated by the golden layer), the electric potential changes between the film and the ground due to the electrostatic induction effect. Free electrons flow from the magnetoelastic conductive film to the ground, driven by electric potential. iii) The BSFS starts to deform by the external object's contact that acts on the magnetoelastic conductive film, further enhancing free electrons flowing from the magnetoelastic conductive film to the ground. Meanwhile, the liquid metal coil (gray) generates a current based on the principle of electromagnetic induction. iv) The free electrons stop moving when the external object finishes the contact stage with the BSFS. v) When external pressure is released, the free electrons flow back from the ground to the magnetoelastic conductive film. At the same time, a reverse current is generated in the liquid metal coil. vi) As the external object leaves the surface of the BSFS, electrons flow back to the magnetoelastic conductive film.

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**Figure 3.** Tactile and touchless sensing performances of the proposed bimodal self-powered flexible sensor (BSFS) prototype. a) The distance between external and BSFS determines the touchless (red) and tactile (blue) outputs. b) The touchless and tactile signals as a function of pressure acted on the BSFS. c) The touchless and tactile output signals at surfaces of different materials. d) The output signals of the BSFS under fast contact stimulus. e) The close-up of the area indicated with the dashed square is shown in panel d). f) Stability and durability of the BSFS under 1000 cyclic excitation periods. Panel g), h) show an image and output signals when tennis drops onto the BSFS. The left light-emitting diode (LED) was programmed to turn on when the tactile signal exceeded a threshold value; the right LED turned on when the touchless signal exceeded a threshold value. Scale bar: 1.5 cm. Error bars represent standard deviation (SD), n = 5 independent replicates.

scenarios. Due to the small noise floor (Figure S8, Supporting Information), BSFS exhibits exceptionally high SNR of 37.4 and 37.2 dB for touchless and tactile signals, respectively. Figure 3f shows the output signals of the BSFS during continuous testing for 1000 cycles under identical conditions, demonstrating its excellent durability and stability. To demonstrate the high dynamic touchless and tactile sensing capabilities of the BSFS, we connected it to a light-emitting diode (LED) control circuit. The touchless signal controlled the lighting of the right LED, while the tactile signal controlled the lighting of the left LED. We recorded the entire process of a tennis ball falling onto the BSFS using a high-speed camera (FASTCAM Mini UX100, Photron Ltd) and measured the corresponding BSFS output signals, as depicted in Figure 3g,h, and Movie S1 (Supporting Information). As the tennis ball gradually approached the BSFS, the touchless signal gradually decreased. The tactile signal suddenly increased when the ball made contact with the BSFS. The touchless signal gradually increased while the ball bounced back, and the tactile signal quickly returned to its initial value. The tennis ball hit the BSFS

six times in less than 1 s and eventually stopped. The results show a high dynamic response of the BSFS.

## 2.2. Intelligent Soft Robotic System Capable of Describing and Sorting Objects

Owing to the simple fabrication process and compatible structure, the BSFS can be easily integrated into soft robots. We combined BSFSs with a metamorphic palm to create an anthropomorphic soft robotic hand, as illustrated in **Figure 4**a. This gripper mimics the dexterity of a human hand, enabling versatile object perception and manipulation. Utilizing the BSFSs as bottom surfaces, we constructed soft pneumatic fingers for the soft robotic hand, as depicted in Figure 4b. The finger exhibits bending motion when compressed air is introduced into its interior due to the corrugated upper surface and relatively high elastic modulus of the bottom structure, as shown in Figure 4c. **ADVANCED** SCIENCE NEWS

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**Figure 4.** The soft robotic hand with bimodal self-powered flexible sensors (BSFSs) identifies the material and roughness of different objects. a) The physical depiction of the soft robotic hand. Scale bar: 3.0 cm. b) A soft pneumatic finger structure diagram with the BSFS as the bottom surface. c) Working principal diagram of the soft pneumatic finger. d) The sensing signals correspond to five materials (nylon, wood, ethylene vinyl acetate (EVA), photosensitive resin, and polyethylene terephthalate (PET)). e) The confusion matrix for identifying different materials (total accuracy: 99%). f) The photograph of the soft robotic hand perceiving the materials of different objects. g) The sensing signal waveforms correspond to six different roughness. h) The confusion matrix for identifying roughness (total accuracy: 97%). i) The photograph of the soft robotic hand perceiving objects' surface roughness.

We incorporated the soft robotic hand onto a robotic arm (AUBO-i5, AUBO-ROBOTICS) to facilitate the material perception. The arm controlled the soft robotic hand to perform touchless scanning on the object, and the signal outputs from the BS-FSs were collected. Figure 4d displays the BSFS output signals of five different materials, each subjected to 20 tests. By training a CNN model using the acquired data, we achieved a remarkable detection accuracy of 99%, as shown in Figure 4e. The material detection results are directly displayed on the screen, as depicted in Figure 4f and Movie S2 (Supporting Information). We also conducted experiments on the intelligent soft robotic system's ability to recognize irregular objects. We identified three common objects with irregular shapes using a touchless scanning method.

The output BSFS signals during the perception of these objects are depicted in Figure S9a (Supporting Information). Each object underwent 20 repeated experimental trials. The results demonstrated that the intelligent soft robotic system achieved a high recognition accuracy, as shown in Figure S9b (Supporting Information). Moreover, the detection results of irregular objects were displayed on the screen (Movie S3, Supporting Information). To perceive the object's surface roughness, we directed the index finger of the soft robotic hand to slide along its surface, capturing the corresponding BSFS output signals. Figure 4g illustrates the BSFS output signals for six distinct roughness levels of the objects (Figure S10, Supporting Information). We conducted 20 detections for each roughness level and employed the collected ADVANCED SCIENCE NEWS www.advancedsciencenews.com

data to train the CNN model. The intelligent soft robotic system demonstrated a high accuracy of 97% in perceiving the roughness of objects, as depicted in Figure 4h. The roughness detection results are directly presented on the screen, as shown in Figure 4i and Movie S4 (Supporting Information). Therefore, the intelligent soft robot system can perceive the objects' surface properties.

When the soft robot interacts with the external objects, the BS-FSs produce intricate sensing signals that capture multiple physical features of the objects. Machine learning has emerged as a powerful approach for extracting and classifying feature information from complex data. CNN shows excellent potential for multimodal information processing among various machine learning algorithms by effectively addressing data format mismatches and subsequent fusion challenges. Therefore, we integrated CNN into our intelligent soft robotic system, as depicted in Figure 5a. Initially, we collected comprehensive information on the materials, shapes, and roughness of the objects involved in the interactions. The collected signals underwent a series of preprocessing. Subsequently, we constructed a CNN model that establishes a relationship between the feature matrix and corresponding labels. This model was iteratively optimized to enhance its performance. As the volume of training data increased, the accuracy of the CNN model's recognition steadily improved. The model precisely perceives and describes the feature information of the objects. Moreover, the soft robot morphs and grasps the objects based on the recognition results of the multimodal sensors.

To facilitate our experiments, we prepared 27 objects which exhibited variations in material (resin, nylon, acrylonitrile butadiene styrene copolymer (ABS)), shape (frame, cylinder, sphere), and surface roughness (smooth, moderately rough, rough), as shown in Figure 5b. For ease of reference and identification, each object was assigned a number. Figure 5c illustrates the accuracy of the intelligent soft robotic system in perceiving and describing the physical characteristics of the 27 objects. Trained by 270 raw data sets, the robotic system achieved an identification accuracy of 97%. Furthermore, we demonstrated the remarkable capabilities of the intelligent soft robotic system in perceiving, describing, and sorting objects based on their physical properties, as depicted in Figure 5d and Movie S5 (Supporting Information).

Specifically, the soft robotic system works by the following steps: i) The soft robotic hand performs a touchless sweep over the object to acquire the BSFSs output signals. ii) Inputting the signals into the CNN model, the intelligent soft robotic system first perceives and describes the object's shape. iii) Subsequently, the system further perceives and describes the object's material. Concurrently, the soft finger glides along the object's surface to perceive its roughness. iv) The system further describes the roughness of the object. Furthermore, we explored the impact of the soft robotic hand's detection speed on the system's detection accuracy. We conducted slow, moderate, and fast detection with 20 repetitions for each speed. The results in Table S1 and Movie S6 (Supporting Information) indicate that the system can maintain a relatively high recognition accuracy even though the soft robotic hand detection speed varies. v) Upon the user's inquiry regarding the roughness value, the intelligent soft robotic system responds. vi) After the comprehensive perception and description of the object's multimodal characteristics, the system prompts the user to indicate the sorting instruction, allowing them to choose based on their preference. vii) According to the shape of the identified object, the system commands the metamorphic palm to assume a specific posture, allowing the soft robotic hand to conform to the object's profile and achieve a stable grasp. These postures have been predefined by researchers based on their expertise. To sort and pick up the frame, the metamorphic palm keeps its original posture, and the fingers are actuated by air pressure (P = 42 kPa). Then the soft robotic hand lifted the frame with the thumb and the index finger. To sort and pick up the cylinder and sphere, the servo controlling the thenar joint rotates inward 60° and 105°, respectively. Then, the servo controlling the metacarpophalangeal joint rotates inward 50° and 60°, respectively. Finally, the fingers were actuated by an air pressure of 50 kPa to catch the object with all four fingers. viii) Ultimately, the system successfully guides the soft robotic hand to deposit the object into the designated box. In conclusion, our intelligent soft robotic system can succinctly describe an object's characteristics, including its shape, material, and roughness, through a single sentence displayed on the screen and transmitted via the loudspeaker. Moreover, our interactive interface facilitates a seamless exchange of inquiries and responses between the user and the intelligent system. For instance, the system can answer user queries regarding the object's properties and effectively sort the object into a specific box per the user's requirement.

#### 3. Conclusion

In this study, we presented an intelligent soft robotic system capable of sensing and describing objects. To achieve this, we designed and implemented the BSFS based on the principles of triboelectric nanogenerator and the giant magnetoelastic effect. The BSFS demonstrated excellent sensitivity in detecting and distinguishing touchless and tactile models, with an impressive response time of only 10 ms. Its simple structure, comprising a magnetoelastic conductive film and a packaged liquid metal coil, made it an integral part of our intelligent soft robotic system. By scanning and sliding on the objects, the gripper system was able to integrate relevant information about their shapes, materials, and roughness. We employed a CNN model to process and interpret the collected sensing information. Through extensive training, the intelligent soft robotic system achieved a remarkable accuracy rate of 97% in perceiving and describing multimodal information.

Despite our proposed design offering several advantages, there are several limitations of the current system that require further efforts. Firstly, the BSFS is limited in its touchless sensing performance, which may be affected by rapid changes in external environmental temperature or humidity. The modality of perception in the intelligent soft robotic system can be further expanded. Incorporating temperature sensing capabilities could be a promising avenue for future research. Additionally, increasing the number of BSFSs in the system would enable the detection of additional information, such as grasp position and pressure distribution. Furthermore, our machine learning model requires further refinement to analyze and process complex multimodal information, aiming to improve feature recognition accuracy. The limitation of the current soft robotic system can be attributed to the algorithms' inability to describe unfamiliar objects. The system can only perform multimodal perception and description of objects it

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Figure 5. The intelligent soft robotic system describes objects' physical properties (material, shape, and roughness) in a language manner. a) The flow diagram of the intelligent soft robotic hand for perceiving, describing, and sorting objects based on their physical properties. b) Photographs of 27 objects with different materials, shapes, and roughness. Scale bar: 5.0 cm. c) Confusion matrix of the system's recognition results with 540 data groups, with a total accuracy of 97%. d) Snapshots of the intelligent soft robotic system's work process. The intelligent soft robotic system demonstrates the capability to perceive and describe various characteristics of objects succinctly, presenting the information in a single sentence displayed on the screen and transmitted via the loudspeaker. Leveraging the interactive interface, the intelligent system can effectively respond to user inquiries and accurately sort the object into a specific box as requested, utilizing the keyboard input.

has been trained on; however, it cannot describe objects outside the training sets. In the future, we intend to further explore intelligent algorithms thus to enhance its level of intelligence. We can enhance the generalization capability of perception systems, enabling them to recognize objects outside the training set, thus expanding the application range of intelligent robotic systems. In terms of the gripper's strength, more efforts should be made to enhance its dexterity and load capacity. By addressing these issues, we can further elevate the interaction of soft robots, empowering them to describe complex objects, meanwhile executing precise manipulation tasks. This work may pave the way for intelligent soft robotic systems with capacities to interpret and interact with the physical world.

#### 4. Experimental Section

Fabrication of the Magnetoelastic Conductive Film: The magnetoelastic conductive film was prepared following the procedure depicted in Figure S1 (Supporting Information). Carbon nanotubes, comprising 0.5% of the total mass, and neodymium-iron-boron micromagnets, accounting for 75% of the total mass, were thoroughly combined in a beaker. Subsequently, Ecoflex 00-30-part A and part B were added to the mixture, which was then vigorously blended using a glass rod for a duration of 10 min. This blending process was crucial for introducing air microbubbles, thereby creating a porous structure within the film. Next, the resulting mixture was carefully poured into a 3D-printed mold, ensuring uniform distribution. The mold containing the mixture was then placed in a heating oven and maintained at a temperature of 80 °C for a period of 4 h to facilitate curing. Once the film had solidified, it underwent magnetization using a magnetizer (WD-80, Yingpu) with a pulsed magnetic field strength of 2.3 T. This magnetization process aimed to induce remnant magnetization within the film, enhancing its magnetic properties.

Characterization of the Magnetoelastic Conductive Film: The crosssectional structure of the magnetoelastic conductive film was examined using a scanning electron microscope (SU8000, Hitachi) to obtain detailed observations. The hysteresis characteristics of the magnetoelastic conductive film were measured by a SQUID magnetometer (BKT-4500, Shin cotest) to analyze its magnetic properties. Furthermore, the strength of the surface magnetic field was assessed using a magnetic probe. The magnetic flux density mappings were measured by a Gauss meter (TD8620, Tunkai) with an axial probe.

Fabrication of the Flexible Liquid Metal Coil Film: Figure S4 (Supporting Information) illustrates the fabrication process of the coil patterns on the substrate. Initially, two coil patterns, forward and reverse, were printed on the substrate using an inkjet printer. Each coil had a side length of 30 mm and a line width of 0.5 mm. Subsequently, liquid metal (Smart800, DREAM Ink) was applied to the printed patterns, followed by a coating of 0.5 mm thick silicone rubber (Ecoflex-00-30). The substrate with the liquid metal and cured silicone rubber was then placed in a refrigerator for 40 min at -140 °C. Afterward, the substrate was carefully removed, resulting in the transfer of the liquid metal coils onto the silicone rubber. The flexible film was divided into two pieces, with one piece coated with a thin layer of silicone rubber, while the other piece served as the cover. The upper and lower liquid metal coils were interconnected through a vertical channel located at the center. Finally, a layer of silicone rubber with a thickness of approximately 1.5 mm was applied to encapsulate the upper liquid metal coil, effectively packaging the flexible liquid metal coil structure.

*Fabrication of the BSFS*: The fabrication process of the BSFS involves applying a magnetoelastic conductive film onto a liquid metal coil using a thin layer of silicone adhesive.

Characterization of the BSFS: The touchless signal output  $\Delta U$  and the tactile signal output  $\Delta I$  were measured using electrometers (Keithley 6514, Tektronix Inc.).

Fabrication of the Soft Robotic Hand: The magnetoelastic conductive film was used to create the bottom surface shape of the soft pneumatic

finger using a 3D-printed mold. It was then attached to a liquid metal coil with a thin layer of silicone adhesive (Sil-Poxy, Smooth-on). The upper surface was fabricated by coating silicone rubber (Mold Star 30, Smooth-on) on a 3D-printed mold with a corrugated structure, and curing it at room temperature for 6 h. The upper surface was attached to the bottom surface with a thin layer of silicone rubber and cured for 4 h at room temperature. As shown in Figure S11 (Supporting Information), the metamorphic palm comprimized a 3D-printed spherical five-linked rod part and two servos. The two servos drove the rotation of the five-linked rod, allowing the palm to change its posture and achieve a human-like function. The soft pneumatic gripper was assembled by integrating the soft fingers into the metamorphic palm.

CNN Model Working Principle: This work applied a series of preprocessing steps for the multimodal signal feedback, including normalization and filtering for touchless signals and cropping for tactile signals. In the material recognition model's preprocess, the raw touchless data were filtered by a low-pass Butterworth filter ( $f_c = 0.2$ Hz, N = 2). In the shape recognition model's preprocess, the raw touchless data were first filtered by a low-pass Butterworth filter ( $f_c = 25$ Hz, N = 2) and then normalized to 0 to 1. In the roughness recognition model's preprocess, the raw tactile data were cropped into 300-frame-long samples randomly in their valuable ranges.

The CNN algorithm could extract specific features in different signal segments by convolutional kernels and achieve the overall signal classification through the features' recognition. CNN could solve the problems of the inefficiency of multiparameter and overfitting. The number of layers and channels of convolutional layers were adjusted in the models to learn different signal features. Each model was trained with 60 datasets to converge stably and achieved high accuracy in online tests for each item.

Statistical Analysis: At least five independent experiments were performed, unless otherwise stated. The results were expressed as the mean  $\pm$  standard deviation (SD) of each set of quintuplicate samples. Statistical analysis was performed using Origin 2023 software.

### **Supporting Information**

Supporting Information is available from the Wiley Online Library or from the author.

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#### **Conflict of Interest**

The authors declare no conflict of interest.

### **Data Availability Statement**

The data that support the findings of this study are available from the corresponding author upon reasonable request.

#### Keywords

convolutional neural networks, giant magnetoelastic effect, multimodal flexible sensors, soft robots, triboelectric nanogenerators

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