Recent developments in robotics increasingly highlight the importance of sensing technology, especially tactile perception, in enabling robots to effectively engage with their environment and interpret physical interactions. Due to power efficiency and low cost, the triboelectric mechanism has been frequently studied for measuring pressure and identifying materials to enhance robot perception. Nevertheless, there has been limited exploration of using the triboelectric effect to detect curved surfaces, despite their prevalence in daily lives. Here, a triboelectric multimodal tactile sensor (TMTS) of multilayered structural design is proposed to recognize distinct materials, curvatures, and pressures simultaneously, thus decoupling different modalities to enable more accurate detection. By attaching sensors to robotic fingertips and leveraging deep learning analytics, the quantitative curvature measurement provides more precise insights into an object’s detailed geometric characteristics rather than merely assessing its overall shape, hence achieving automatic recognition of 12 grasped objects with 99.2% accuracy. The sensor can be further used to accurately recognize the softness of objects under different touch gestures of a robotic hand, achieving a 94.1% accuracy, demonstrating its significant potential for wide-ranging applications in a future robotic-enabled intelligent society.

1. Introduction

In recent years, notable progress has been observed in the field of robotics. This progress stems from the integration of artificial intelligence (AI) algorithms with robotic systems, facilitating enhanced capabilities in perception and autonomous decision-making within complex environmental contexts. Such as object recognition, human-machine interaction, etc. Central to these advancements is the indispensable role of sensing technology, which facilitates the effective interaction of robots with their surrounding environment. While considerable attention has been devoted to refining visual perception capabilities in robotic systems, the study of tactile perception emerges as an equally significant area, offering promising avenues for interpreting physical interactions with objects with heightened dexterity and sensitivity.

To achieve humanoid robotic tactile sensing and mimic biological human sensory systems, various tactile sensing mechanisms have been frequently investigated. Conventional methods include resistive sensors, capacitive sensor, and optical fiber, widely used as strain sensing, static and dynamic forces monitoring, and temperature detection, etc. With the progress of functional materials, there are research regarding self-powered transduction mechanisms like piezoelectricity, thermoelectricity, and triboelectricity. Studies have illustrated the distinct advantages of these mechanisms in terms of power compatibility, especially considering the considerable power consumption of current AI robotics and their sustainability in unplugged working scenarios. Lee et al. reported an e-skin to identify stimuli such as pressure and tensile strain on the basis of triboelectricity and piezoresistivity. Jin et al. introduced a soft robotic manipulator enabled by a triboelectric nanogenerator tactile sensor for contact area and position sensing and a triboelectric nanogenerator length sensor for bending motion measurement. With the help of machine learning (ML), various types of sensory data are analyzed with high precision. Xiong et al. have utilized ML for the analysis of the sensing signals to assist human motion monitoring. Additionally, the concept of multimodal perception further enhances the anthropomorphic robot’s sensory abilities by combining multiple sensing modalities and bringing more useful features, providing a comprehensive understanding of external world. For instance, Li et al. integrated pressure, material thermal conductivity, and bimodal temperature signal detected by a quadruple tactile sensor to perceive the shape, material, and texture of objects. A soft manipulator system reported by Sun et al. fulfilled a fusion...
of tactile, strain and temperature sensory signals, thus providing more comprehensive information of the grasped objects.\[40\] Here, ML can automatically extract the useful information and the data fusion strategy leverage the complementary effects of different sensor modalities, thus enhancing the sensing and recognition accuracy, as well as the system robustness.\[41\]–\[43\]

Due to the desirable features of simple structure, fast response, low cost, and diversified material choices,\[44\]–\[46\] triboelectric nanogenerator (TENG) has been widely studied for tactile sensing\[47\]–\[52\] since its first announcement by the Wang et al. in 2012.\[53\] For example, Bu et al. reported a stretchable triboelectric-photonic smart skin on a robotic hand that measures vertical pressure sensing.\[54\] Wang et al. developed a pressure-sensitive triboelectric sensor matrix for the visualization of touch actions or tracking motion trajectories.\[55\] In addition to pressure detection, material recognition is another important aspect of tactile perception. When diverse materials come into contact, variations in their electron affinity lead to differences in their ability to gain or lose electrons.\[56\]–\[58\] As a result, the TENG mechanism can be used to identify the contacted material by analyzing distinct triboelectric output signals. Compared to other common approaches like vision technologies,\[59\]–\[60\] using TENG to recognize material requires less cost, simpler fabrication, and lower data complexity. Several approaches have been explored to identify material based on TENG.\[61\]–\[62\] Qu et al. created an intelligent robotic finger with a sensor array that enables the identification of materials and roughness.\[63\] The computation of voltage ratio between the differently positioned sensors can effectively reduce impact of environmental interference on the triboelectric signal of each sensor. Combining pressure and material recognition, Zhao et al. presented a multifunctional tactile sensor employed on robots for object recognition.\[64\] Wang et al. integrated triboelectric, thermoelastic and piezoresistive sensing mechanisms to achieve pressure, temperature and material sensing simultaneously.\[65\]

While significant research has been conducted on the tactile functionality of TENG, these efforts have predominantly focused on planar contact scenarios. In terms of curvature, which are important features of objects, present works mainly emphasize on capturing the general shape of the object with the help of ML.\[66\]–\[67\] with minimal attention given to quantitively identifying the curvature of the contact point. Developing an augmented object recognition system, which distinguishes between objects with similar shapes, requires a focused approach on sensing the local curvatures of objects. Integrating ML techniques to combine the detected curvature with additional information such as material and pressure paves way for more accurate object identification. Therefore, a highly integrated multifunctional tactile sensor capable of simultaneously detecting pressure, material, and curvature emerges as an essential and innovative solution for enhanced object recognition systems.

Here, we propose a triboelectric multi-modal tactile sensor (TMTS) designed to intelligently recognize material, curvature and pressure at the same time. The size is only 17 mm × 12 mm × 3 mm, with two functional elements integrated. A paper and a surface textured Ecoflex with three columns are dedicated to pressure sensing at its base (Figure 1). Positioned atop the Ecoflex and paper are the contact element comprising three materials, each arranged along one column. These materials include one Polyimide (PI) film and two Polytetrafluoroethylene (PTFE) films, which concurrently fulfill the functions of material discrimination and curvature detection. The paper and Copper (Cu) connected to ground, sandwiched between the two functional elements, act as a shielding unit to prevent interference between the two functional elements. The highlight of this work is its ability to decouple different modalities including materials, curvatures, and pressure simultaneously through simple contact-separation movement. Besides, it is novel that TMTS enables quantitative curvature interpretation of the contact point within a compact size. By affixing these sensors to multiple fingertips of robotic hands, the detection of curvatures and materials can evolve into object recognition tasks. Particularly noteworthy, the quantitative curvature measurements offer more detailed insights into an object’s shape. This enhanced precision enables a more accurate distinction between objects sharing similar general shapes but differing curvatures. Feeding the detected material, curvature, and pressure signals into a deep learning algorithm, we ensure highly precise and robust object recognition system across a wide range of applied forces. Furthermore, by analyzing the detected pressure and curvature, TMTS can be further developed to identify the softness of an object.

2. Results and Discussion

2.1. Working Mechanism and Design Strategies of TMTS

Figure 1a displays the structure of TMTS, which consists of seven layers: the top two layers, comprising of PTFE, PI and Cu, serve as the contact element for material and curvature sensing; the bottom three layers, consisting of paper and Ecoflex with three columns on its surface, are used for pressure sensing. Paper and grounded Cu are additionally inserted between the contact element and pressure measurement layers. This functions as a shield, preventing the upper and lower parts from interfering with each other. Figure 1b provides a detailed depiction of this multi-modal measurement. For material identification (Figure 1bii), P1 (Channel 1) and PTFE (Channel 3), are positioned on the leftmost and rightmost sides of the sensor. Upon contact, two different TENG waveforms will be generated across Channel 1 and Channel 3, due to PI’s and PTFE’s distinct abilities of gaining or losing electrons. Computing the voltage ratio between Channel 1 ("Channel" denoted as “C" in Figure 1) and Channel 3, \( R_{mat} = \frac{V_{C1}}{V_{C3}} \), enables precise indication of the relative position of the detected material on the triboelectric series. Due to symmetry, these two films have the same contact area with the curved object, thus isolating the influences of various curvatures and enhancing the precision of material discrimination. For curvature identification (Figure 1biii), two PTFE films are placed in the center (Channel 2) and rightmost side (Channel 3) with the material held constant. Differing in their contact area with the object, two distinct TENG waveforms will be generated across Channel 2 and Channel 3. As both contacting with PTFE, variations in measured TENG signals are exclusively attributed to differences in contact area as well as the pressure with the object. Additionally, recognizing that pressure can influence TENG signals, the lower layers (Channel 4, Channel 5 and Channel 6), which is comprised of Ecoflex and paper is utilized for pressure measurement...
Figure 1. Overview of the triboelectric multimodal tactile sensor (TMTS). a) Configuration of TMTS enabled intelligent robotic finger. Top: Illustration of TMTSs attached to robotic fingers. Bottom: Material composition of TMTS. b) Working mechanism of TMTS in (i) material identification, (ii) curvature measurement, and (iii) pressure measurement. Left: Structural characteristics of functioning components. Right: Quantitative measurement of functioning components (C1 is the abbreviation for Channel 1. The same applies for C2-C6) and their typical signals. c) Computation approaches to ensure minimal mutual impact between different sensing modalities. d) Schematic diagram of the sensing system from (i) human perception level (contact with the object and cloud deep learning data analytics via AI brain) and (ii) multi-finger data fusion, preprocessing and feature extraction (material, curvature, shape, deformation, softness) enabled by deep learning.
Rmat, Rcurve and pressure map, are collected in real-time by the material, curvature, and pressure. The detected signals, including temperature, when the four robotic fingers contact with an object, each effects between various modalities. In our robotic sensory system, object recognition system, thanks to the complementary sensory fusion process. This approach of biological multimodal data computation from initial organs undergoing the somatosensory primary connection between the human perceptive organs and cerebral cortex, clearly described in the Methods.

At the systemic level, four TMTSs are attached to four robotic fingers: index, middle, ring, and pinky. The system mimics the connections between the human perceptive organs and cerebral nervous system (Figure 1d), where the tactile sensory information from initial organs undergoes the somatosensory primary area (PA), association area (AA), and then the biological multisensory fusion process. This approach of biological multimodal data analysis has been proven effective in helping to achieve an augmented object recognition system, thanks to the complementary effects between various modalities. In our robotic sensory system, the four robotic fingers contact with an object, each TMTS on the corresponding finger detects signals related to material, curvature, and pressure. The detected signals, including Rmat, Rcurve, and pressure map, are collected in real-time by the IoT module and transmitted to the cloud server for multimodal fusion and deep learning based data analytics to finally fulfill a highly accurate object recognition system. Within the data system (Figure 1dii), the signals from four TMTSs are integrated and preprocessed before being inputted into the deep learning architecture. Subsequently, through deep learning, features are extracted from the 6 channels of each TMTS, reflecting the material and curvature of the object’s local area. With all 24 channels on 4 robotic fingers, the shape of the object can be identified. Furthermore, by analyzing the detected pressure and curvature, the softness of an object can be inferred due to the object’s deformation. These features are then used for object classification. The circuitry diagram is provided in Figure S1 (Supporting Information).

2.2. Curvature and Material Characterization of TMTS

A TMTS generates six signals denoted as Channel 1 through Channel 6, achieved through the contact and separation mechanisms of TENG (Figure 2a). The mapping between these six channels to their respective materials is described in Table S1 (Supporting Information). Channel 2 and Channel 3 capture the curvature characteristics of a contact object. Upon contact with an object, the two PTFE films exhibit a tendency to attract electrons, driven by differences in electron affinity. This leads to a change in electrical potential across the Cu electrodes (Figure 2b). When separated, positive charges are induced across Cu electrodes, driven by differences in electron affinity. This leads to a further explanation of this TENG working mechanism is provided in Figure S2 and Text S1 (Supporting Information). The influence of varying contact areas between the contact element and the object is depicted in Figure 2c, with the relative voltage amplitude of each PTFE film shown in Figure 2cii. Initially, in step 1 (Figure 2cii), only PTFE on the left is in contact with the object, so most current flows through Channel 2. When the contact object shifts to the right in step 2, the object’s contact area with the PTFE on the right increases, so the output voltage of Channel 3 rises. Meanwhile, the PTFE on the left remains in full contact, thus maintaining a constant output voltage at Channel 2. Moving to the third step, the object fully engages with both PTFE films, resulting in Channel 2 and Channel 3 reaching their maximum voltage values simultaneously, which are equal. In step 4 and 5, the contact area between the object and the left PTFE film diminishes, causing a decline in output voltage at Channel 2. Meanwhile, the PTFE on the right remains in full contact, thus maintaining a constant output voltage at Channel 3. Hence, this reflects that a larger contact area between the PTFE film and the object results in an increased triboelectric signal output. Figure 2d illustrates the difference in contact area between objects of various curvatures and TMTS. To simplify, the curves are characterized using the parameter d, representing the distance from the lowest point to the point at a distance of r from the centroid (Figure 2d). While maintaining r constant, an increase in d from 0 mm to 100 mm results in a reduction in the contact area between the object and two PTFE films, with PTFE on the right decreasing in a faster rate. This pattern is evident in the output voltage observed in Channel 2 and Channel 3, as demonstrated in Figure 2e, where a general decline is observed. It is noteworthy that the output voltage of Channel 2 increases when d increases from 0 mm to 25 mm. This arises from the significant increase in pressure caused by the reduction in contact area. As d further increases from 25 mm to 50 mm, the influence of contact area on the triboelectric signal becomes more pronounced, reflected in the declining output voltage in both Channel 2 and Channel 3. Wherein, the greater decrease in the voltage of Channel 3 is due to the more significant reduction in contact area of the PTFE on the right. When d increases beyond 75 mm, there is minimal contact area between the object and the PTFE on the right, resulting in a negligible voltage amplitude across Channel 3.

Materials have varying tendencies to gain or lose electrons when contact with each other. The triboelectric series categorizes materials based on their relative tendencies to gain or lose electrons. By observing the charge acquired by a material when it contacts with a known material from the triboelectric series, its relative position in the series can be inferred. This can help identify unknown materials based on their triboelectric properties. In this setup, PI and PTFE are used to identify the material of contact object due to their distinct electron affinities. According to the triboelectric series, PTFE exhibits stronger electronegativity compared to PI, resulting in a higher accumulation of output charges on its surface, as shown in Figure 2f. This distinction is apparent in Figure 2fii, where the peak output voltage of PTFE exceeds that of PI. To isolate the influences of various curvatures, PI and PTFE are positioned on the leftmost and rightmost sides of the sensor to keep the contact area with the object the same. In this case, a precise discrimination of material via voltage measurement in Channel 1 and Channel 3 can be achieved. Figure 2fii illustrates the diverse waveforms produced by TMTS when contacting five different curved materials, with Aluminum (Al) being the most electropositive and PET being the most electronegative. Notably, when the TMTS contacts the same material, the voltage of Channel 1 consistently remains lower than that of Channel 3, confirming PTFE’s higher electronegativity. This can also be
Figure 2. Characterization of curvature measurement and material identification. a) Overview of the functionalities of the six channels in TMTS. b) Working mechanism of TMTS curvature measurement. c) (i) Illustration and (ii) relative voltage output of TMTS having varying contact area with the object under contact force of 30 N. d) Illustration of TMTS contacting with objects with varying curvatures ($d = 0$ mm, 25 mm, 50 mm, 75 mm, 100 mm). e) Output voltage of Channel 1, Channel 2 and Channel 3 within TMTS when contacting with objects with varying curvatures. f) (i) Working mechanism of TMTS material identification. (ii) Output voltage signal for Cu contacting with PI and PTFE. (iii) Triboelectric signals (Channel 1 and Channel 3) within TMTS for the 5 identified materials. (iv) Voltage amplitude of Channel 1 and Channel 3, and voltage ratio of the two channels computation of 5 materials.
inferred from the voltage signal generated across Channel 1 and Channel 3 in Figure 2e. Furthermore, a smaller discrepancy in electronegativity correlates with a lower amplitude of output signals, as seen in the decreasing voltage amplitude from Al to PET. To further determine the position of the contact material on the triboelectric series, Figure 2f presents the voltage ratio of Channel 3 to Channel 1. As the difference in electronegativity diminishes, an evident decrease in the ratio is observed, indicating the TMTS’s effective discrimination of materials. Another advantage of this voltage ratio computation is that it is unaffected by varying pressure, which will be further discussed later sections. Besides, TMTS also demonstrates exceptional capability in isolating the influence of diverse curvatures during material identification and the effect of varying materials during curvature measurements as shown in Figure 2e, Figures S4, and S5 (Supporting Information). Hence, the contact element of TMTS shows its outstanding ability in decoupling curvature and material, while ensuring that one modality does not interfere with the other.

2.3. Effect of Varying Pressure on TMTS’s Curvature and Material Measurement

Based on the fact that increased pressure generates larger triboelectric signal, triboelectric mechanism is employed for pressure measurement.[69] The surface textured Ecoflex (Figure 3ai) serves as negative triboelectric material and paper serves as positive triboelectric material (Figure 3aii). The voltage induced in Channel 4, Channel 5 and Channel 6 corresponds to the pressure applied to Channel 1, Channel 2, and Channel 3 respectively. Note that an insulating layer which is composed of paper and Cu connected to ground is inserted between the curvature and material measurement element and the pressure measurement element to prevent them from affecting one another. The electronegativity of the shielding material, paper, closely matches that of Cu to prevent any unintended charge transfer due to the triboelectric effect. Figure 3b,c demonstrate that increasing pressure leads to an increase in the output voltage amplitude of Channel 4, Channel 5, and Channel 6, with a sensitivity of 0.1 V N\(^{-1}\) when contact object is flat.

Similarly, greater pressure also increases output voltage amplitude of Channel 1, Channel 2, and Channel 3, corresponding to material and curvature signals. Despite the ascending trend of voltage amplitude across Channel 1 and Channel 3 with increasing pressure (Figure 3d), the voltage ratio of Channel 1 to Channel 3 remains approximately constant (Figure 3e). This indicates that variations in pressure do not exert influence on material identification. On the other hand, Figure 3fi reflects that that alterations in pressure have an impact on curvature measurements, demonstrated by a distinct trend wherein the voltage amplitudes across Channels 2 and Channel 3 rise at varying rates (0.025 V N\(^{-1}\) and 3.5 V N\(^{-1}\), respectively). This occurs because a greater force applied to TMTS accompanies with an increase in contact area between the object and TMTS. Hence, it is challenging to distinguish merely from these two channels that whether the increasing triboelectric signal is attributed to the decrease in curvature or the greater pressure. Considering this, the corresponding pressure signals (Channel 5 and Channel 6) are taken into consideration. Results show that the voltage amplitude of the pressure signal in Channel 5 is increasing at a similar rate of 0.024 V N\(^{-1}\) with that of Channel 2 (Figure 3fi). Similarly, the voltage amplitude of the pressure signal in Channel 6 increases at a similar rate of 4 mV N\(^{-1}\) with Channel 3. Hence, the detected pressure signal can be used to counteract the effects of varying pressure on curvature measurements by computing the ratio of absolute differences between corresponding voltage pairs, \(R_{\text{curve}} = \frac{|V_{\text{Channel 2}} - V_{\text{Channel 1}}|}{|V_{\text{Channel 5}} - V_{\text{Channel 4}}|}\). As shown in Figure 3g, this ratio is constant despite variations in pressure, showing the necessity of pressure sensing and the robustness of TMTS. The effectiveness of TMTS in decoupling different sensing elements is illustrated in Figures S7–S10 (Supporting Information), with \(R_{\text{mat}}\) being constant at different curvatures and pressures. \(R_{\text{curve}}\) is constant at different materials and pressures. The sensitivity of pressure at different curvatures across Channel 4, Channel 5 and Channel 6 are provided in Figure S11 (Supporting Information). The sensitivity of curvature measurement is 145 mV mm\(^{-1}\), provided in Figure S12 (Supporting Information). All TENG signals exhibit a similar response time of approximately 63 ms, as illustrated in Figure S13 (Supporting Information). The durability test results are displayed in Figure S14 (Supporting Information), where Cu repeatedly contacts Channel 1 of TMTS with a consistent force of 30 N. These results indicate that the output voltage of the TENG signal remains stable after thousands of cycles, demonstrating the durability and stability of the TMTS. The reproducibility of the TMTS (Figure S15, Supporting Information) and low power consumption (Text S2, Supporting Information) reflect TMTS’s good performance.

2.4. Object Classification Via Curvature and Material Recognition using Multiple TMTSs

Due to the automatic feature extraction and generalization capability, deep learning has been shown effective for extracting features from the time-domain data of triboelectric signals and high-precision identification of different samples.[70,71] Leveraging signals from diverse sensing modalities, deep learning models can identify intricate TENG signal patterns, such as voltage magnitude, direction, and temporal sequences, as well as the relationships between different channels and TMTSs. This advanced analysis facilitates a comprehensive understanding of the information, leading to more accurate predictions. Hence, all modalities of TMTS are integrated and fed into deep learning architecture to perform recognition tasks. As depicted by the schematics in Figure 4a, the sensor is attached to the robotic finger for TENG signal collection. Subsequently, all TENG signals undergo a preprocessing circuit aiming at filtering out the ambient noise and amplifying the collected signal. Next it will enter the MCU which detects the equivalent analog signal of output voltage and transmit the data to a PC. The data then undergoes cleaning and further preprocessing before deep learning. Long Short-Term Memory (LSTM) architecture is employed due to its notable ability to handle sequential data. In training phase, data is fed into the LSTM model, and the model learns to make predictions based on the input features. The model’s parameters are adjusted iteratively using optimization algorithms to minimize the loss between the predicted outputs and the
actual targets. During testing, accuracy and confusion matrix will be used to evaluate the classification performance. Each input sample fed into the LSTM model comprises a three-dimensional matrix, with the axes representing the time sequence, different channels, and the output voltage at various time steps and channels (Figure 4b). Consequently, the dimension of the input tensor is time sequence length $t \times$ number of channels $m \times$ number of samples $n$. The architecture consists of a LSTM layer with $k$ hidden sizes and a fully connected layer. Finally, it will output simultaneous predictions for curvature and material.

To illustrate the capability of classifying curvatures and materials concurrently, TMTS is attached to a single robot fingertip to establish a data set containing 12 objects with three distinct curvatures and four different materials (Figure 4c). The robotic finger repetitively contacts and separates with the 12 objects for 100 iterations (Figure 4d) with various pressure. The resultant data set with three-dimensional information is presented in Figure 4e. Here, $t = 150$ and $m = 6$. The 100 samples of each object are randomly divided into training, validation and testing set at a ratio of 6:2:2. The outcome of the test set is showcased in Figure S16 (Supporting Information), with an accuracy.
Figure 4. Deep learning-enabled curvature and material dual-labelled classification. a) Schematic diagram of signal collection, data processing, and model training and testing process. b) Structural diagram of LSTM model consisting of LSTM layers and fully connected layers. c) Illustration of 12 objects with three distinct curvatures (d = 0 mm, 25 mm, 75 mm) and four different materials (glass fiber, Al alloy, PC, and PVC). d) Illustration of TMTS contacting with curved material. e) The typical 6-channel output spectra collected by TMTS as the input of the deep learning algorithm. Columns of 6 channel spectra labeled as 1–12 from left to right corresponds to the signal of touched objects labeled as 1–12. f) TSNE illustration of (i) 12 objects in general, 12 objects classified by (ii) curvature and (iii) material.
Figure 5. Deep learning enabled object recognition system. a) 12 objects to be recognized by the system. b) Illustration of the 24 channels measured during sensing and input into the LSTM model. c) The typical 24-channel output spectra collected by TMTS as the input of the deep learning algorithm. Columns of 24 channel spectrums labeled as 1–12 from left to right corresponds to the signal of objects labeled as 1–12. d) Illustration of different contact position of objects with various shapes. e) Confusion matrix of the classification outcome.

of 95.8%. Furthermore, Figure 4f shows a visualization of the dataset using the t-distributed stochastic neighbor embedding (t-SNE) algorithm which utilizes a nonlinear dimensionality reduction technique to project high-dimensional data for into a low-dimensional one with two or three dimensions. Notably, in Figure 4fi, all data points are clustered according to their respective subgroups, with clusters sharing the same material or curvature positioned closer together, indicating the similarity among corresponding data points. Figure 4fii,iii illustrates that object clusters with different curvature and material can be divided into separate planes. This underscores the robust performance of the TMTS-LSTM combination in achieving simultaneous classification of curvatures and materials.

To demonstrate the object classification capability of TMTS, we selected 12 daily items (Figure 5a). The four sensors are attached to four robotic fingers respectively. With six channels on each finger, there is a total of $4 \times 6 = 24$ channels (Figure 5b). Hence, $m = 24$, and $t$ is chosen to be 170. The robotic hand repetitively grasped each of the 12 objects for 150 iterations under varying pressure conditions, with the resulting triboelectric signals
plotted for each object in Figure 5c. Each TMTS attached to a finger discerns the curvature at a particular contact location on the object, thus employing four TMTSs aids in capturing the overall shape of the object (Figure 5d). Considering that the robotic finger does not know the exact contact position, we made small adjustments to the position and angle of objects during data collection. By leveraging deep learning, the system learns the relationship between the triboelectric signals on the four fingertips, resulting in a more robust system and more accurate object identification. This approach allows for greater flexibility and reduces the dependency on precise and fixed grasping points. Utilizing 60% of the dataset for training, 20% for validation, and 20% for testing, the model achieved an accuracy of 99.2%. From the confusion matrix (Figure 5e), most objects can be recognized with 100% accuracy, even though some objects share similar shapes like object ①, ②, and ⑤. This underscores the robust performance of TMTS, as quantitative curvature measurement provides more precise and detailed information about the shape of an object compared to simply measuring its general shape. This precision allows for more accurate characterization and differentiation between objects with similar overall shapes but slightly different curvature profiles. TMTSs can also be applied to nonuniform and nonconformal surfaces. Deep learning is capable of understanding the intricate relationship between the triboelectric signals generated on the different fingertips of the robotic hand without special compensation. This sophisticated learning process enables the system to become more robust, maintaining its performance even when the TMTS makes contact in a nonconformal manner. However, the robotic hand still needs to know the general position and direction of the target object. For future work, ultrasonic sensors may be included in the system for auto-positioning to realize a completely automatic object grasping and recognition system.

2.5. Object Softness Sensing with TMTS

Softness perception is also an emerging research direction in the field of tactile perception. The characterization of softness can also be implemented via TMTS by examining the correlation between the applied force and the resulting curvature deformation of a material. Hence, Channel 2, Channel 3, Channel 5, and Channel 6, which are indicative of curvature and pressure, are utilized to analyze the softness level of an object. A data set containing 6 cylinders is established with three softness levels and two distinct materials, Al and Cu (Figure 6a). Take the three cylinders attached with Al as an illustration, the different softness levels are achieved by 3D printing via varying materials and different wall thicknesses. As shown in Figure 6b, the most rigid level (object ①) is constructed via 3D printing using polylatide (PLA). The intermediate softness level (object ②) is 3D printed using thermoplastic polyurethane (TPU) with a wall thickness of 2 mm. The softest level (object ③) is fabricated through 3D printing using TPU and a wall thickness of 0.5 mm. Maintaining a constant force applied by the robotic hand, the voltage amplitude of Channel 2, Channel 3, Channel 5 and Channel 6 exhibit a declining trend (Figure 6c), indicating a reduction in the detected pressure by TMTS as the softness level increases. At the same time, the value of \( \frac{V_{\text{Channel 2}} - V_{\text{Channel 5}}}{V_{\text{Channel 1}} - V_{\text{Channel 6}}} \) decreases, suggesting a reduction in curvature with increased softness of the object (Figure 6cii). These observations are consistent with the fact that the softest object undergoes the most significant curvature deformation under minimal applied force (Part 2.1 of Video S1). Fixing the softness of an object, an increase in the applied force (Figure 6dii) results in greater deformation, as evidenced by reduced curvature (smaller value of \( \frac{V_{\text{Channel 1}} - V_{\text{Channel 5}}}{V_{\text{Channel 1}} - V_{\text{Channel 6}}} \)) shown in Figure 6diii and Part 2.2 of Video S1.

In addition, the objects are subjected to two different touch gestures: without thumb (w/o-T) and with thumb (w-T) (Figure 6e). Take object ③ as an example, the voltage amplitude increases when the robotic hand grasps the object with thumb (Figure 6fii), indicating that grasping object with thumb imposes extra pressure to the object. Simultaneously, it induces greater deformation, resulting in a smaller curvature detected by TMTS from Figure 6fiii and Part 2.3 of Video S1. For the 6 objects, the data of two touch gestures of each object are fused together, and then input into an LSTM architecture yielding an accuracy of 94.1% (Figure 6g), demonstrating a robust recognition system even when grasping with different touch gestures. The TSNE illustration shows that TMTS has a good recognition of softness (Figure S20, Supporting Information). With the ability to evaluate softness, pressure, material, and curvature, TMTS opens up several exciting applications across various domains. In applications such as automated sorting systems or assembly lines, it can facilitate the efficient sorting and classification of objects based on their physical properties. In extreme environments such as space exploration and disaster response scenarios, where robots are deployed to navigate unknown terrain or search for survivors in debris, TMTS can aid in object detection and localization.

3. Conclusion

We present a triboelectric multimodal tactile sensor (TMTS) which is able to discriminate variations in material, curvatures, and pressure based on simple contact-separate movement of robotic fingers. The different voltage output signals generated in P1 and PTFE films enable discrimination of materials. Further supported by the voltage ratio, TMTS is able to identify the contact material under varying pressure. Contact between a curved object and two PTFE films induces different amount of electron transfer across them due to the variations in contact area. By factoring in the corresponding pressure signal, the voltage ratio can be calculated to mitigate the impact of fluctuating pressure on curvature measurements. Hence, TMTS offers a novel capability for quantitative curvature interpretation within a compact size. At the same time, great robustness is achieved due to its ability to recognize materials and curvatures under varying pressure conditions. All the functionalities are implemented on a minimalistic sensor, showing its high integration. Incorporated into multiple robotic fingers and leveraging deep learning techniques, TMTSs can detect the materials and curvatures of the contact points, thus achieving automatic classification of objects. This highlights the augmented performance of TMTS on object recognition, as its quantitative curvature measurement offers more detailed insights into an object’s shape, enabling more precise distinction among objects that share similar overall shapes but distinct curvatures. The system achieves a remarkable 99.2% accuracy in automatically identifying grasped objects, hence
Figure 6. Object softness sensing with TMTS. a) 6 cylinders with three softness levels (from left to right) and two distinct materials (top: Al, bottom: Cu). b) Configuration of objects with different softness levels. c) Diagram of (i) output voltage amplitude and (ii) computed curvature measurement of object ①, ②, and ③ with varying softness under same applied pressure. d) Diagram of (i) and (ii) output voltage amplitude and (iii) computed curvature measurement of objects with the same softness level (object ③) under different applied pressure. e) Illustration of different touch gestures of robotic hand. (i) without thumb (w/o-T) and (ii) with thumb (w-T). f) Diagram of (i) and (ii) output voltage amplitude and (iii) computed curvature measurement of objects the same softness level (object ③) under different touch gestures. g) Confusion matrix of 6 objects with two different touch gestures (contacting with thumb: 1-w-T – 6-w-T and contacting without thumb: 1-w/o-T – 6-w/o-T).
showcases their potential for practical applications. TMTS can be further developed to identify the softness of an object by analyzing the applied force and the resulting curvature deformation, reaching an accuracy of 94.1%. With these capabilities, TMTS holds the potential in a wide range of applications, such as automated sorting systems and exploration in extreme environments. We hope that this work can inspire further research directions that can focus on recognition on curved objects.

4. Experimental Section

Fabrication of TMTS: The triboelectric textile sensor contains seven layers: paper and Ecoflex for pressure sensing and the contact element for curvature detection and material identification. First, solution A and B of Ecoflex™ 00–50 with a ratio of 1:1 by weight was mixed thoroughly for 5 minutes and then poured into a 3D-printed mold. The mold was then placed into the oven at 70 °C for 20 minutes for curing. The cured Ecoflex was attached to three columns of Cu films, with a small amount of mixed Ecoflex solution used for adhesion between the solidified Ecoflex and the Cu films. Three materials (consisting of one PI film and two PTFE films) were initially adhered to one side of the Cu films and while the other side was attached with one Cu layer nestled between two layers of paper. All eighteen films had a dimension of 5 mm × 12 mm. Subsequently, they were joined to the lower part using a mixture of Ecoflex for adhesion, with additional reinforcement provided by needles and thread.

Experiment Measurement and Characterization: Analog voltage signals were measured and calibrated with an oscilloscope (DSO-X3034A, Agilent), using a high impedance probe of 100 MΩ. All the cured parts were 3D printed and different materials are attached to the curved parts for material discrimination characterization. TMTS was attached to the force gauge (Mecmesin, MultiTest 2.5-i) with the speed of 400 mm min⁻¹ for measurement. During characterization of curvature measurement and material identification, a constant force of 30N was controlled by the force gauge. The robotic hand used during data collection was a commercial dexterous hand RH56BFX-2R from Inspire Robots and was controlled using Python. After the measurements, Python was also used for data cleaning and preprocessing. The LSTM models were built in Python with Tensorflow framework. For all classification tasks, cross entropy loss was employed as loss function, Adam optimizer as optimizer algorithm and StepLR as learning rate scheduler. The values of hyperparameter k for the three classification tasks are provided in Table S2 (Supporting Information).

Supporting Information

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

Acknowledgements

X.Z. and Z.S. contributed equally to this work. The work was supported by NRF-CRP28-2022-0038 “Integrating Wideband Tuneable Acoustic Filters on Silicon for High-Speed Wireless Communication” (WBS: grant no. A-8001503-00-00) at National University of Singapore (NUS), Singapore, and RIE2025 IAF-ICP under I2301E0027 “Piezo Specialty Lab-in-Fab 2.0 (LIF 2.0) – Enabling Unrivaled Power Efficient Transducers Beyond Material Limits” at National University of Singapore (NUS), Singapore.

Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Keywords

artificial intelligence, object recognition, tactile sensing, triboelectric

Received: June 3, 2024
Revised: July 20, 2024
Published online:
