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Haptic-feedback smart glove as a creative human-machine interface (HMI) for virtual/augmented reality applications

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Human-machine interfaces (HMIs) experience increasing requirements for intuitive and effective manipulation. Current commercialized solutions of glove-based HMI are limited by either detectable motions or the huge cost on fabrication, energy, and computing power. We propose the haptic-feedback smart glove with triboelectric-based finger bending sensors, palm sliding sensor, and piezoelectric mechanical stimulators. The detection of multidirectional bending and sliding events is demonstrated in virtual space using the self-generated triboelectric signals for various degrees of freedom on human hand. We also perform haptic mechanical stimulation via piezo-electric chips to realize the augmented HMI. The smart glove achieves object recognition using machine learning technique, with an accuracy of 96%. Through the integrated demonstration of multidimensional manipulation, haptic feedback, and Al-based object recognition, our glove reveals its potential as a promising solution for low-cost and advanced human-machine interaction, which can benefit diversified areas, including entertainment, home healthcare, sports training, and medical industry.

INTRODUCTION

Human-machine interfaces (HMIs), as a window of communication between the user and the particular equipment, robot, or virtual world, are the key elements for achieving effective, intuitive, and seamless manipulation to complete the tasks. With the aid of advanced technology, the solutions of HMI switch from the conventional control terminals, such as keyboard, touchpad, and joystick, to more diversified and creative alternatives. As a result, more realistic interactions between users and machines eventually satisfy the additional needs beyond the simple controlling of objects, such as virtual social networking. For instance, voice control is widely applied in mobile phones, smart cars, and homes to execute verbal commands (1), while vision recognition can identify facial features and realize human motion capture (2). Furthermore, wrist bands containing electromyographic electrodes can record hand gestures (3), and electroencephalogram (EEG) electrodes are even able to detect human intentions directly, i.e., by detecting brain wave (4). However, some of these technologies expose several limitations in the applications of virtual reality (VR) and augmented reality (AR), for example, both vision and voice recognition struggle to detect fine features, such as finger motion. Hence, wearable glove-based HMIs have the unique advantages of high precision and multiple degree of freedom (DOF) control.

By using wearable glove-based HMI, hand motion could be projected into machine, robot, or devices in the VR and AR space.

This kind of technology can be an important complementary solution to vision and voice recognition as well; hence, a considerable amount of the controlling tasks could be realized. Moreover, subtle, emotional, and detailed interaction between human and human and human and machine could be realized with the aid of gestures and hand motions. More specifically, there are several important parameters required to capture the comprehensive information from hand and deliver it to the controllable objects. Currently, the finger bending actions are the most commonly measured data, and the detectable DOFs and sensitivities become the guidelines of fabricating the desired data glove. Besides, the identification of shear force (5), i.e., the lateral directional motions, gradually becomes another research interest as per the requirement of recording the entire interactive forces for the use of external tool to enhance the manipulations from various HMIs. Meanwhile, a series of feedback techniques are also necessary to establish an immersed experience and improve our sensing capabilities toward the remote or virtual objects.

One of the most matured techniques is to apply the inertial sensors including an accelerometer and a gyroscope. Relying on the high sensitivity of those microelectromechanical system (MEMS) sensors, smart gloves usually feature highly sensitive motion tracking, and the DOF is determined by the number of sensors (6). However, to detect the applied force, additional sensors are required, which usually lead to complex circuit and data processing for different types of signals. Another commercialized solution for smart gloves is to use resistive sensors (7). The strain, normal force, and shear force can be quantitatively measured using specific designs, such as meandered and spiral-shaped channels (8). In addition, the resistive sensors are capable of sensing both the static and dynamic force continuously as well. But these sensors also experience drawbacks from the temperature effect, zero shift, and creep issues, which need further corrections. Recently, attempts to use optical sensing have also been reported (9). The proposed devices mainly detect the deflection of incident light from a diode to recognize finger bending.

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The major challenge will be the limitation of detectable bending angle within the deflection range of incident light. In general, those available glove products reveal their own drawbacks, and many of them rely on the introduction of unique designed sensors to achieve advanced control which are not completely ready yet. Therefore, improvements of the HMI glove still require the implementation of other emerging technologies.

Development of materials sciences facilitates research studies on the sensing of physiological signals (10-11). Numerous designs of soft and stretchable electronics have been reported, such as wavy shaped and gold or silver nanofiber based. In addition to conformability, different sensing mechanisms have also been studied widely, such as transistor-based (12), resistive-based (13), and capacitivebased (14) sensors for detecting strain, static force, and dynamic force, or even the slippery motions with high sensitivities (15). In the meantime, various nanogenerators, as devices that convert the diversified ambient energy into electricity, are frequently studied in recent years (16). For instance, a piezoelectric nanogenerator can scavenge the mechanical stimulus via the polarization of the dipole moment. For triboelectric nanogenerator (TENG), it refers to the charge transfer during the mechanical interactions of two materials with dissimilar electronegativity. Both of the two phenomena are frequently used to fabricate the self-powered tactile sensors now, as they can reduce the power consumption of the entire system. Lead zirconate titanate (PZT) (17) and polyvinylidene fluoride (PVDF) (18) were piezoelectric materials widely adopted for fabricating the tactile sensor array or flexible sensors on wearable devices. However, some constraints still limit the practical applications, such as low output for soft PVDF material, and too brittle for PZT chips. Alternatively, on the basis of high flexibility of customization and the low cost for triboelectric-based sensors, different designs have been proposed in studies of motion tracking (19), pressure mapping (20), and two-dimensional (2D)/3D space controlling (21). As a costeffective wireless solution of wearable HMI, our preliminary research studies have reported using arch-shaped strips attached to the finger joint to enable the bending detection and generate the pulse signals (22). Furthermore, the sliding mode of the grating structure improves the resolution of the bending angle by detecting the pulse peaks (23).

On the other hand, the stretchable and epidermal sensors with multipixel and multifunctional sensing array are frequently studied to mimic the entire function of human skin (24-25), i.e., large-area instantaneous pressure mapping (26) and neural receptors for mechanical and temperature stimulus (27). However, the enormous amount of generated data that consume more computing power will be another problem, which may not be necessary for all of the normal interactive applications. Eventually, a proper data analysis strategy is expected to be a solution of HMI for minimalistic design.

The rapid development of machine learning from artificial intelligence (AI) paves the way for strengthening the functionalities of sensors without substantial effort on device upgrading (28, 29). By leveraging the proper learning model for specific sensing application, more comprehensive information can be extracted for those simply designed sensors, such as motion sequences, touch forces, and slipping (30). On the basis of the training of the output pattern from the grabbing or touching behavior on different objects, gesture and object recognition can be realized instead of the primary simple motion detection. This will not only directly benefit the humanmachine interaction but also allow the smart glove to establish a database for supporting the research of anthropomorphic robot (31). For establishing a smarter system using the fusion of sensing and feedback functions, the mechanical stimulator for haptic feedback is crucial to reflect the interactive event in the virtual world. A well-designed feedback system can enrich the experience and assist the user to make adjustments. Several approaches were then explored, such as vibration motor (32), microfluidic or pneumatic chamber (33), and wire actuator (34). These techniques can more or less enable the feeling of impact events or even the shape of objects, but the bulky size of the whole actuation system and the power consumption become the critical problems for portable and continuous use. As an alternative, the application of piezoelectric material as embedded mechanical stimulator can be considered as another choice (35) due to its much smaller size and lower energy consumption, which is highly desirable for long-term users.

Generally speaking, for the manipulations in the VR/AR and for the advanced robots, a glove with multidimensional sensors and well-designed haptic feedback are essential to achieve the precise control via immersed experience and comprehensive sensation. Here, we present a smart glove consisting of elastomer-based triboelectric tactile sensors and PZT piezoelectric haptic mechanical stimulator (Fig. 1) as a simple and cost-effective approach for intuitive HMI. The 3D-printed glove case (Fig. 1i) is designed to support the sensors and mechanical stimulators for multidimensional motion detections and real-time haptic feedback. The major functional units of triboelectric tactile sensors include the finger bending sensors, which can detect the motions of each phalanx with multiple DOFs, and the palm sensor that can sense the normal and shear force in eight directions (Fig. 1, i to v). The proposed smart glove can realize the joint advanced manipulation, in which the real-time impact event can also be delivered back via piezoelectric haptic stimulation (Fig. 1vi) for enhancing our sensation against the indirect interaction. This will also benefit the rehabilitation of disabled patients by monitoring the practice activities and offering a certain stimulation. Moreover, to expand more functions with minimized number of sensors, the machine learning technique offers the possibilities of performing complex tasks using the proposed glove, such as object recognition. For the applications of VR/AR, this glove can be functionalized as the complementary control interface in addition to the current vision and voice control terminal for augmented interactions. Hence, a promising solution with low economic and technical cost for advanced HMI is developed, which can benefit industrial productivity, educational training, entertainment, and home care.

RESULTS

Design of smart glove

First, Eco-flex (00-20) is used as the elastomer material for fabricating the finger sensor with a hemisphere shape, and the aluminum electrode is encapsulated at the flat side (see fig. S1). The as-fabricated sensors are bonded inside the individual finger case by epoxy (Fig. 2A). The distributions of sensors are defined by the available DOFs of three phalanges of fingers: distal phalanx (DP), middle phalanx (MP), and proximal phalanx (PP), because both DP and MP can only have upward or downward bending, where PP is able to deflect to the other directions. Hence, the number of sensor arrangement of two, two, and four corresponding to DP, MP, and PP, respectively, is decided. The palm sensor at the center (Fig. 1, i and iv; also see fig. S2) is applied to enable the detection of normal force and shear force when contacting with external object. Unlike the finger



Fig. 1. Schematics of glove-based HMI for diversified applications. (i) Three major functional units: triboelectric finger sensor and (ii) the working principle for (iii) detecting bending motions, triboelectric palm sensor, and (iv) the working principle for (v) detecting sliding motions, as well as piezoelectric haptic mechanical stimulator for (vi) haptic stimulation.

sensors, the electrode pads feature four quadrants and separated from the above elastomer membrane with about 3 mm. For this elastomer membrane, the top layer is made by polydimethylsiloxane (PDMS) with one large dome shape of 15 mm diameter, and there are four Eco-flex-based small hemispheres (3 mm) located at the bottom layer as the touching point against the below four electrode pads (see fig. S2). On the other hand, five PZT thin chips (Fig. 1, i and vi) are placed at the root of each finger for performing the haptic feedback.

To assemble all the separated finger cases with palm case, the metallic alloy wires with certain restoring force were used as the connector so that the entire case can be supported under the pressure of bending and enabling the deformation of the elastomer sensor.

Working principles

For both finger and palm sensors, as mentioned earlier, the triboelectric output is generated from the contact electrification during the surface interaction between two dissimilar materials. Hence, in terms of multiple sensors applied on the glove, the triboelectricbased sensors with self-generated signals can reduce a considerable amount of power consumption. The reported devices usually used two external materials to conduct either the contact and separation of the arch-shaped structure (*36*) or the sliding of grating patterned strips (*23*). In this work, the skin is used as a positive triboelectric material to contact with negative sensors that can effectively reduce the entire size of device while achieving the detection of additional DOFs. As shown in Fig. 1i, triboelectric sensor usually shows two opposite pulse waveforms that correspond to either contact or separation cycle, depending on which side the output signal is extracted. In the proposed glove, the finger sensor relies on the interaction between elastomer and finger skin. At the original state, the sensor is at its neutral state, where the surface negative charges are balanced by positive charges from the embedded electrode pad. Switching the contact state, as skin is much more electrically positive compared to elastomer, the positive charges from the skin surface neutralize the negative potential at the sensor surface and cause the previous positive charges on the electrode pad to be repulsed to the ground. Hence, when the output signal is measured from the electrode pad, the positive pulse can be observed due to the current flow direction. In contrast, the separation between finger and sensor will then lead to the returning flow of positive charge on the electrode pad to neutralize the negative sensor surface and generate a negative signal.

For the palm sensor, as illustrated in Fig. 1ii, the external impact on the top dome will cause the deformation of the entire membrane, and the direction of deviation is related to the shear force, i.e., forward sliding motion will cause the forward sensor to deform more than the other three sensors and result in a larger triboelectric output



Fig. 2. Schematics and characterization of triboelectric finger bending sensors. (A) Designs of finger case of each phalanx, the positions of sensors, and the photo of the PP. (B) Comparison of triboelectric outputs of sensor made by PDMS and Eco-flex. (C) Characterized relationship between the changing loading force and the triboelectric output of sensor under 2-Hz frequency. (D) Variations of triboelectric outputs with different sensor sizes (diameter: 3, 3.5, and 4 mm) for a finger size of (i) 60 mm and (ii) 50 mm in perimeter. (E) Measured triboelectric outputs from eight sensors (DU, DD, MU, MD, PU, PD, PR, and PL) under the bending of (i) DP, (ii) MP, (iii) PP, and (iv) all three phalanges (curling). The dashed boxes indicate the functional signals. (F) Measured triboelectric outputs from four sensors (PU, PD, PR, and PL) under the bending of finger in eight directions: (i) up, down, left, and right and (ii) up + left, up + right, down + left, and down + right. Photo credit: Minglu Zhu, National University of Singapore.

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as an indication of shear force direction. The palm sensor uses the elastomer and the electrode as the negative and positive material, respectively. The electrode will extract positive charges from the ground to balance the negative charge on the elastomer during contact, and hence, a negative output is generated instead of positive for finger sensor. In general, it is important that this work uses the positive signals from finger sensor and the negative signals from the palm sensor as the sensing signals for further application.

To perform the haptic mechanical stimulation (Fig. 1vi), the converse piezoelectric effect is applied on the PZT chips. Once the command of interaction event was triggered, the microcontroller will send the pulse width modulation (PWM) signal with resonant frequency to actuate the vibration of chips, and the intensity can be tuned by the supplied power to reflect the degree of interaction.

Device optimization and characterization

In Fig. 2A, the design of the finger sensor together with the printed finger cases is illustrated. To ensure the sensitivity of signal and the comfortability of long-term use, two common biocompatible materials are investigated: Eco-flex and PDMS. As the comparison test is shown in Fig. 2B, for the same dimension of hemisphere of 4 mm diameter, the output of 200 mV for Eco-flex is much larger than that of PDMS, which is preferable for conducting accurate sensing. According to triboelectric theorem, the generated output is mainly determined by the contact area for the same materials due to the amount of interacted surface charge. The output response against the applied force was then characterized (Fig. 2C). For a 3.5-mm sensor, a typical sensing range from 0.1 to 3.5 N was obtained under 1.5-Hz pressing, and the maximum detectable force is defined by the largest area between the deformed sensor and finger for contacting. This range is also considered as the reference for choosing the stiffness of connection wires, which exert restoring force during finger bending. Furthermore, the size effect of the sensor was studied with three samples of different diameters: 3, 3.5, and 4 mm. The output shows an increasing trend as the size becomes larger (Fig. 2D). However, the perimeters of human finger are quite different throughout a large population. For a specific size of finger case and the user, there is always an optimized configuration for the highest output as depicted from Fig. 2D (i and ii), because the limited inner space will set the constraints for the contact and separation process, i.e., bigger finger will experience less contact and separation motion that lead to less surface charge interaction. Owing to the unique design of separated finger cases, each joint of the glove can be replaced and customized to achieve the desired performance. In this work, the participant used 3.5 mm as the dimension for all the finger sensors.

Triboelectric output signal characterization of finger sensor

As shown in Fig. 2E, the index finger was tested with a series of common motions to investigate the sensing capabilities of as-fabricated finger sensors. On the basis of three segments of index finger, six sensors are designed for upward and downward bending: DU, DD, MU, MD, PU, and PD. In addition, the left and right bending sensors, named PL and PR, are added for PP. For the tests of individual phalanx (Fig. 2E, i, to iii), the signals of major functional sensors are highlighted in the dashed box. On the basis of the stiffness of the chosen elastomer, the response time is around 30 to 40 ms. To ensure the distinction among different bending angles, the primary resolution of each phalanx is set to 30° according to the obtained data with the reasonable tolerance of data error. The DP shows two angles due to the real motion range of human finger. Similarly, for the experimental data of MP and PP, there are still minor signals detected from DD and MD except for the major functional sensor, especially for the larger bending angle. This phenomenon was caused by the controlling capability of the actual motion of individual phalanx for a specific user, and it is frequently observed that the phalanx at the front will also be bent unintentionally during the bending of the mindle phalanx or PP. All of these were also detected by finger sensors, and the minor output was then generated. In Fig. 2Eiv, as an advantage of multiple sensors, the curling motion of the PP. From the data of three dashed boxes, it is obvious that both the DD and MD for curling shows signals above the active threshold, and there are only negligible outputs observed for DD and MD in bending motion.

As mentioned earlier, the joint of PP has more DOF compared to the other. Hence, eight directions are tested, including four standard directions of up, down, left, and right, and four diagonal directions of up-right, down-left, up-left, and down-right. First, the functional sensors and the output signals are depicted accordingly (Fig. 2F). It is worth mentioning that all of the four sensors are measured simultaneously so that the signals of the theoretically inactivated sensor pairs can be monitored for the potential interferences, as the finger was barely contacting with all the sensors at the original state. The measured data (Fig. 2Fi) indicate that there is almost no interference between the two pairs of counter sensors, PR/PL and PU/PD. That is, although the finger may slide across the surface of PU/PD when performing left and right motion, the contacted surface area is actually maintained the same and leads to very low charge transfer based on triboelectric theorem. For four diagonal directions, each direction can be detected using two adjacent sensors that are marked as well. As the contact force is distributed over two sensors, the decrease of output from ~150 mV to less than 100 mV is also noticed.

Demonstration of real-time virtual hand control and mouse control

As a primary verification of the HMI function, the detected triboelectric output signals were used to project the motions of human finger into the virtual hand in Unity with frame per second (FPS) of 60. The external circuit of reading multiple triboelectric signals consists of a microprocessor with multichannel analog inputs and a customized conditioner printed circuit board for preprocessing the triboelectric signals before the input channels (further described in fig. S6 and text S2). For a typical example of index finger bending, the real-time signal waveforms of eight sensors were monitored. As mentioned before, the thresholds of specific bending angles were calibrated for the sensors from each phalanx, such as the dashed black lines on the signals of PD. As an example of 30°, a positive triboelectric signal from PD was generated when bending the PP and pressing PD, and a negative signal was also recorded on PU due to the separation event that has no function in this case. Next, the returning motion of the PP led to the pressing of PU and induced a positive signal, while the separation of PD gave a negative signal. In terms of demonstration program, once the signal reaches the threshold (Fig. 3Ai), the program in the microprocessor will send the corresponding code out, i.e., "0,0,1,0,0,0,0,0" and "0,0,2,0,0,0,0,0" for 30° and 60° bending of PD, respectively, where the positions of each number stand for different sensors. Meanwhile, the program of Unity can receive the code as a command via communication protocol of



Fig. 3. Demonstrations of finger bending sensing as main functions of HMI. (A) (i) Projection of the motions of PP in virtual space (FPS: 60) and the corresponding positive triboelectric outputs from eight sensors (DD, MD, PD, DU, MU, PU, PL, and PR) on index finger with three distinguishable bending angles (30°, 60°, and 90°) and the following returning motion detected by positive signals of PU for each bending, (ii) projection of the motions of index finger with three phalanges under DP bending, DP + MP bending and DP + MP + PP bending, and the following returning motion detected by positive signals of PU for each bending, (iii) projection of the motions of IDU, MU, and PU for each bending, as well as left/right deflection of the PP. The dashed lines and boxes indicate the functional signals. (**B**) Screenshots of the demonstrations of (i) alphabet writing and (ii) online shopping, (iii) schematics of the detailed procedure of alphabet writing, with photos of finger motions and the corresponding triboelectric output signals for (1) activate dragging, (2) upward writing and stop, (3) down + right writing and stop, (4) upward writing and stop, (5) activate moving, (6) right moving and stop, (7) activate dragging, and (8) downward writing and stop. Photo credit: Minglu Zhu, National University of Singapore.

serial port and converted it into the motion of virtual hand. For the validation of multiple DOF manipulation (Fig. 3Aii), similar to the characterized data in Fig. 2, the functional signals are marked in dashed boxes, and all the upper sensors—DU, MU, and PU—are in charge of returning motion. On the basis of the real-time signal waveforms, each bending activity was performed with a cycle of bending and returning. For instance, with the curling motion (bending of DP + MP + PP), all three bending sensors were triggered,

with DP and MP reaching the threshold of 60° and PP reaching the threshold of 30°, which were projected into the virtual hand. Then, all three returning signals from DU, MU, and PU were activated to set the finger back to the original state, and there was only a unified low threshold for these upper sensors to simplify the returning process. In general, the triboelectric outputs in practical application proved to be consistent with the experimental data during characterization and showed a good signal quality with low noise. Hence,

the proposed glove with triboelectric sensing mechanism is a promising solution of conducting the dexterous manipulation of virtual hand as a complimentary device for the conventional vision and voice recognition.

As a basic function of glove-based HMI, except gesture projection, the replacement of conventional mouse control is also important to minimize the complexity of the whole system of manipulation. By converting the index finger into a virtual pointer to initiate the motions of cursor, the glove-based mouse control was realized with the demonstration of online shopping and alphabet writing (Fig. 3B, i and ii, and movie S1). In addition to the motions of eight directions using the four sensors of PP of index finger, the functions of scroll, drag, and click are assigned to middle finger and thumb, respectively. As shown in Fig. 3Biii, the dragging mode was initiated by the positive peak from the bending of the thumb detected by DD (step 1), and the index finger was then used to write the alphabet (step 2). For the writing process, the positive and negative peaks corresponding to bending and releasing actions were responsible for the commands of start and stop, respectively, and the diagonal writing (step 3: down + right) was achieved by pressing both PD and PR sensors based on the writing motion of finger. After finishing the first alphabet, the thumb was then returned back and DU was pressed to initiate the moving mode of cursor (step 5), in which the motions were again controlled by the index finger (step 6). In general, by using the glove with the proper programming, the intuitive interaction can be realized, which can minimize the learning cost compared to other systems with multiple controllers.

Triboelectric output signal characterization of palm sensor

Except for recognizing the finger motions of hand, the detection of external interactions from the additional tools is expected to enhance the controlling experience for VR/AR. The design of the palm sensor is shown in Fig. 4A. Typically, there are two important parameters to define the categories of interactions, including the normal force and the shear force. Additionally, because the palm sensor used the negative elastomer hemisphere to contact the bottom electrodes, and the negative triboelectric outputs collected from the electrodes become the functional signals as shown in Fig. 4C. As the proposed palm sensor, the normal force can be determined by the amplitude of the negative triboelectric output as shown in Fig. 4B. As most of those interactions are not the contacts in pure normal direction, the four-quadratic design of the palm sensor is then used for simultaneous measurement to identify the lateral direction of the applied force, i.e., the shear force as decomposed part. In this case, we defined the four standard directions: upward, downward, forward, and backward based on the straight fingers pointing toward the front and the center of palm pointing to the left or right side. The output data in Fig. 4C indicate that a total of eight directions can be detected, including the four standard directions sensed by each quadrant of the electrode pad individually, and the other four diagonal directions measured by two adjacent quadrants. In Fig. 4D, by sliding the palm sensor across the object, the demonstration using virtual hand shows the functions of defining the trends of the entire hand motion. For example, the downward sliding of the palm sensor induces the contact of the electrode in charge of downward sensing and the separation for the electrode of upward sensing at the opposite side and leads to one negative and one positive signal, respectively. For the diagonal motions, such as up + backward, the sliding caused the contacts of two adjacent electrodes for sensing up

and backward motions and the separation from two opposite electrodes and, hence, generated two positive and two negative signals. Meanwhile, it is worth mentioning that the characterized data were tested under the pure lateral force exerted on the top dome to obtain the featured outputs. The practical scenarios usually engage with the combination with both the normal and shear force, for instance, a typical forward pushing will generate not only the signal from the forward sensor but also some smaller signals from other three sensors. Hence, in the programming part, the comparison code for the triboelectric outputs from four electrodes is implemented to assist the identification, i.e., the direction judgment is conducted if one or two outputs show much larger amplitude than the others.

Characterization of piezoelectric haptic mechanical stimulator

PZT chips as piezoelectric components were applied using the converse piezoelectric effect to transform the electrical PWM input into the mechanical stimulation with the tunable intensity by controlling the input voltage from 6 to 12 V. The resonant frequency is determined as 270 Hz based on the dimensions (Fig. 4E). Three levels of intensities are set for activation of mechanical haptic stimulation in demonstration as illustrated in Fig. 4F. As a validation, two PZT chips were bonded together, and one of them was used to convert the mechanical stimulation back into electricity via piezoelectric effect. Hence, the real-time stimulation can be visualized during the demonstration. As depicted in Fig. 4G, the module of collision reactor in Unity allowed us to deliver the virtual collision events back into the microcontroller through the serial communication and to activate the mechanical stimulation by programmed PWM input. As a result, the contacting and releasing events can then be fed back to the user immediately with tunable intensity to distinguish them.

Integrated demonstration in baseball game program

For all of those data glove-based HMIs, the ultimate goal is to create an intuitive and immersed interaction for either controlling the real robots or the virtual characters. Hence, the multidimensional detections of human actions incorporated with well-defined haptic feedback are the key to the research of HMIs. In this work, to verify the practical use of the proposed glove, an integrated demonstration was prepared through the baseball game program to perform the manipulation of the baseball bat and the haptic stimulation from the strike event (Fig. 4, H to J, and movie S3). In Fig. 4K, the logic loop of conducting the game program includes several main steps. First, the program entered into the preparation mode for operational check of triboelectric sensor. Next, the grabbing action was detected by both the finger sensors and the palm sensor once the real bat was grabbed and the program was switched into the play mode in which the autopitching machine started the pitching loop. The triboelectric outputs from the palm sensor were detected with the same amplitude for all four electrodes, which indicated only the normal force applied during the grabbing. Noticeably, except the negative peaks used as sensing signals, there were also unnecessary positive peaks that were mainly caused by the first contact between the bat and the glove and would not be obvious after grabbing the bat. Then, at the autopitching stage, the user could swing the bat with different speeds to have a strike, and the reactive force exerted on the palm sensor induces different triboelectric outputs accordingly. Figure 4 (I, iv, and J, iv) illustrates that the swinging actions of bat lead to



Fig. 4. Triboelectric palm sensor and piezoelectric haptic stimulator. (A) Design and photo of as-fabricated palm sensor. (B) Characterization of the output against the loading force from a single electrode at 2 Hz. (C) Measured triboelectric outputs from four electrodes for sliding in eight directions: (i) up, down, forward, and backward and (ii) down + forward, up + backward, down + backward, and up + forward. The activated signals are in dashed boxes. (D) Control of virtual hand 793 by interacting with external objects in eight directions. (E) Design and photo of PZT haptic stimulator. (F) Measured stimulation using second PZT chip for tunable input AC power (6, 8, and 10 V) at 270 Hz. (G) Demonstration of real-time haptic feedback in response to the interactive event in Unity, with the measured mechanical stimulation. (H to K) Integrated demonstration in baseball gaming program. The illustrations of (H) grabbing bat, (I) light strike, and (J) heavy strike with (i) screenshots of real-time demonstration in Unity, (ii) measured haptic stimulation induced by the piezoelectric stimulator, (iii) measured triboelectric outputs from the palm sensor, and (iv) the intensity of interactive force exerted on each electrode and the shear force direction. (K) Flow chart for the operation of baseball program. Photo credit: Minglu Zhu, National University of Singapore.

nonuniform distribution of contact triboelectric output on four electrodes due to the existence of the shear force. As an example of heavy strike (Fig. 4J), both forward and upward electrodes show the larger triboelectric output compared to downward and backward electrodes. From the schematic of pressure mapping in Fig. 4Jiv, by inspecting the trend of output variations, the directions of shear force caused by relative motions between bat and hand are defined because the top dome of the palm sensor is pushed toward forward + upward direction and leads to the membrane deflecting more toward the contact of electrodes of forward and upward. The resulting shear force direction is presented as the arrow mark. As a result, the corresponding notable outcomes were performed in the training program, i.e., ground ball or fly ball. Meanwhile, the collision event between ball and bat was fed back into the microprocessor and activated the mechanical stimulation via PZT chips with the aid of collision reactor module. To differentiate the various strikes, the input voltage for actuating the stimulators can be tuned depending on the measured triboelectric output of the palm sensor during swinging.

Unlike the current data gloves that are mainly equipped with the finger bending sensors and the corresponding vibrational haptic motors, the proposed glove with the sliding sensor and haptic stimulation enriches the available sensing dimensions for the humanmachine interactions so that the projection of our activities become more realistic in the diversified scenarios that require more advanced and dexterous manipulations.

Application of machine learning on object recognition

Recent advances in the HMI lead to the study on different types of object recognition techniques for developing a more intelligent system. There are a considerable number of research studies that emphasize on the optical or ultrasound-based 3D object recognition. In terms of wearable tactile sensors, several designs have also been reported to achieve the recognition function, and most of them feature the dense array of microsensors on the glove to scan the surface structure and stiffness. As a tradeoff, these devices usually require high computing power and complex processing circuit while they can offer more accurate recognition for different objects. As an alternative solution for the proposed glove with much fewer sensors, machine learning provides a promising method for deeply analyzing the detected triboelectric outputs and extracts the useful patterns from different events (*28*, *37*).

As a primary test on machine learning-based object recognition using triboelectric outputs, there were 16 sensors from the glove that were monitored simultaneously. Considering the finger usage for the most cases, the 16 sensors include thumb (DD and DU), index finger (DD, MD, PD, and DU), middle finger (DD, MD, and PD), ring finger (DD, MD, and PD), pinky finger (DD, MD, and PD), and palm (single electrode), as the thumb and the index finger are the most frequently used fingers. Six objects with various shapes were chosen to be grabbed, and the triboelectric outputs from the grabbing of the rod, cube, disk, curved structure/moon, pyramid, and small cube, were recorded. Unlike the other recognition strategies for triboelectric outputs (38-39), which analyzed the detailed features in a single waveform, such as frequency, holding time, latency, and gaps of peaks, in our work, the combined dataset from 16 channels can form a spectrum to provide enough features to be extracted automatically using machine learning; hence, the raw data that contain various important information in a dynamic grabbing process, e.g., finger bending speed, contacting force between fingers and sensor

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arrays, sensors' triggering sequence, and the operation manners for a specific user, can be fed into the training model directly without the preprocessing step, i.e., normalization and segmentation. That is, the general features of signal patterns across the entire 16 sensors were more important.

Deep learning is becoming a very popular subset of machine learning due to its high level of performance across many types of data. The reported study has successfully used multiple deep belief networks to extract features adaptively from the raw signals of triboelectric keyboard and realized keystroke dynamic identification (28). Another great way to use deep learning to extract features automatically and reduce data complexity simultaneously is to build a convolutional neural network (CNN). A 1D CNN is a very effective method to derive interesting features from shorter (fixed length) segments of the overall dataset in which the positions of the features within the segment are not of high relevance and, hence, applies well to the analysis of time sequences of sensor data. As illustrated in Fig. 5A, the parameters used to construct the CNN model are labeled, and the detailed information can be seen in table S1. For the training sample collection, each of the 16 sensors had 200 data points recorded per sample to train the model for recognition. For each object, 500 samples were collected for training (80%) and testing (20%). In Fig. 5B, the typical triboelectric outputs for grabbing all six objects are shown, with the featured patterns marked in black dashed boxes. Compared to the reported glove (40) with dense arrays of resistive sensors using CNN to evaluate the mapping of the static pressure during the grabbing activities of different objects, the proposed glove with triboelectric sensors focuses on the investigation of the dynamic changes along with the complete cycle of grabbing. As the number of sensors is limited, the basic working mechanism of object recognition is not defined by the detection of shape, and the human hand usually cannot cover the whole object. That is, the outputs from the glove actually indicate the grabbing habits on a specific object for a specific user, i.e., the participant uses five fingers to grab cube and uses three fingers to grab small cube, which result in additional outputs from the sensors of ring and pinky fingers for cube grabbing. As another example, although all five fingers were used for grabbing both rod and cube, the shape of object led to the different bending states of each finger, which generated the dissimilar waveforms to distinguish two objects. More specifically, the variations of signal waveforms, such as the activated channels, sequences of peaks, and amplitudes, are affected by several elements that are mentioned before. As another commonly used machine learning method, support vector machine (SVM) has been widely used as classifiers in various applications of pattern recognition. Because of the large dimensions of acquired data samples, which was 3200 for each sample (200 data points from each of 16 sensors), the principal components analysis (PCA) method was used to extract the features and reduce the dimensions of data, and the kernel function was applied as the linear function. More specifically, two parameters are important for obtaining the suitable model, data dimensions and the penalty parameter C, which is used to determine the possibilities of misclassification. According to the trials of optimization using linear kernel and radial basis kernel for classification (see table S2) and the concern of computing power, the dimensions of data were set to be 300 for achieving enough accuracy of recognition. The confusion map of models in Fig. 5C shows that both of the two methods can assist the glove to achieve above 96% accuracy of object recognition (single run) with 400 training samples for each



Fig. 5. Triboelectric output-based object recognition using machine learning technique. (A) Schematics of the process and parameters for constructing the CNN. (B) Corresponding triboelectric outputs from 16 sensors: thumb (DD and DU), index finger (DD, MD, PD, and DU), middle finger (DD, MD, and PD), ring finger (DD, MD, and PD), pinky finger (DD, MD, and PD), and palm (single electrode), during the grabbing of six objects, including rod, cube, disk, curved, pyramid, and small cube. The solid boxes indicate the featured pattern for the training of recognition. (C) Confusion maps of object recognition derived from two models made by (i) CNN and (ii) SVM, with 100 tests for each object and 40 tests for the baseline; output class refers to the recognized results, and target class refers to the true objects. Photo credit: Minglu Zhu, National University of Singapore.

object. Among them, there are few groups showing the relative lower accuracy, such as 94% of rod and pyramid from the CNN model (Fig. 5Ci), with the four outputs falling into the cube and the three outputs falling into the curved structure, respectively. By observing the triboelectric output patterns in Fig. 5B, some similarities can be found among them. For rod and cube, the main difference is the signal from the palm sensor, and there will be a false judgment if it is too small during one grabbing. Similarly, for the curved and pyramid structure, the signals from ring and pinky fingers are the main features, and the abnormal amplitude of signals from the grabbing of pyramid will lead to false judgment. Meanwhile, in the SVM model, a 91% accuracy is obtained for pyramid recognition as well, as six samples are identified as curved due to the same reason. Hence, to ensure the stability of performance for irregular human motions, except increasing the sample population and tuning the grabbing force, it is also important to change the positions of the signals in time domain to cover the whole segment of collection window. The comparable results indicate that, for a small amount of sample data with enough distinguishable features, SVM can also offer a good accuracy of recognition. Meanwhile, the CNN model usually has better performance for the large amount of data with similar patterns, as CNN can automatically extract the features rather than the manual selection. Generally, both of the trained recognition models developed from CNN and SVM methods performed well in our experiments. Through the manual extraction of features using PCA, the classification of the SVM-based model is already good enough. Meanwhile, for the CNN method with more advanced function of automatic extraction, the proposed glove only requires a relatively simple network to realize the high performance. As a primary demonstration, the SVM-based model was selected for conducting real-time object recognition (movie S2).

Integrated demonstration in VR surgical training using object recognition

The promotion of VR/AR technologies also paves a new way for the diversified training program that can benefit the medical, industrial, and educational fields by saving the cost markedly. Hence, the functionalities of HMIs play an important role to satisfy the requirements of achieving various operations. In addition to the previous demonstration of baseball game, the proposed glove can be further enriched via the introduction of machine learning technique and other programmable functions. As depicted in Fig. 6 (A and B), a pair of gloves were fabricated for conducting the demonstration of VR surgical training program and AR-based human-humanoid interactions (movies S4 and S5). In this case (Fig. 6C), the left glove is assigned to enable the motions of the entire arm and hand and the switching of the operation modes, whereas the right glove is applied for object recognition and surgical operation. By switching into the recognition mode using the left index finger, the left glove is then disabled, and the right glove enters into the recognition mode for recording the signals of grabbing gestures. In terms of recognitions of three selected tools, the specific triboelectric signals from the grabbing actions are shown in Fig. 6Dii. For example, thumb and index finger were applied for operating the scissors, which led to the signals from the sensors of thumb and index finger only, but for grabbing the gauze, the additional signals from the middle finger were detected as three fingers were used. After the specific tool is successfully recognized, the gloves are then switched back into the control mode, in which the left thumb and middle fingers can

relocate the virtual arm to the operation area, and the right glove will conduct the surgical operation accordingly. The corresponding triboelectric outputs are shown in Fig. 6D, with the photos of functioning fingers of the glove. For an example of knife operation demonstrated in movie S4, the left ring finger was bent and returned to display and hide the left hand by triggering the positive triboelectric signals of the ring finger (DD and DU) [Fig. 6, C (IV) and Di (IV)]. The left index finger then bent to trigger the recognition mode via index (DD) [Fig. 6, C (I) and Di (I)]. During the recognition data collection from the right glove, the right hand mimicked the grabbing actions of knife, and the surgical knife was successfully recognized and presented in the VR space [Fig. 6, C (VI) and Dii (VI)]. Next, the left index finger returned back to trigger the control mode via index (DU) (Fig. 6, CI and 6DiI). Next, the left thumb and middle finger were used to move and rotate the right hand to the operation zone [Fig. 6, C (II and III) and Di (II and III)]. Last, the right middle finger triggered the cutting operation of knife [Fig. 6, C (IX) and DI (IX)].

Although there are only finger sensors and palm sensor, this demonstration still verifies the potential of applying this facile designed glove to realize the advanced multipurpose manipulations in addition to the vision-based motion tracking in the 3D space. In addition, the object recognition technique can greatly simplify the entire process.

DISCUSSION

Smart gloves, as a frequently studied HMI, act as a bridge that connects humans with the virtual world and machines. How seamless we can perform the interaction highly depends on the available functions of the glove. Although the proposed gloves consist of only three units including triboelectric finger sensors, palm sensor, and piezoelectric haptic stimulators, the devices can still be capable of performing the jobs in a great variety without integrating the conventional inertial or resistive sensors, such as the VR surgical training. Moreover, by leveraging the AR techniques, more intuitive interaction regarding the communication with the virtual characters can be accomplished using this glove, such as handshaking and cheers (Fig. 6B and movie S5). As a result, except the usage on training, the proposed glove can eventually turn into a terminal for initiating the virtual social network. Especially for the elderly, more interactive communication will definitely enhance the emotional comfort during the remote home care from doctors or family. In addition, for a long-term operation, it is also possible to realize the complete self-powered system by implementing the TENG modules or hybrid energy-harvesting modules on the major motional positions of the human body to collect the kinetic energy and develop the proper power management unit.

Overall, a smart glove with facile designed triboelectric sensors and piezoelectric haptic mechanical stimulator indicates the potential of constructing a low-cost and low-power consumption HMI that is capable of achieving multidimensional and multipurpose manipulations in VR/AR. The high customizability of the glove ensures user-friendliness and signal stability regarding the variety of human hands. Compared to the commercialized HMI of vision recognition, the glove can act as a complimentary solution to offer the hapticfeedback functions. In addition, although finger motion can also be detected via camera using machine learning, the sensing of sliding interaction between the two objects still requires the glove-based



Fig. 6. Integrated demonstration in VR/AR applications. (A) Illustration of functions for the as-fabricated gloves under control mode and recognition mode. (B) Universal applications on diversified scenarios. Augmented interactions for various VR training programs and social activities using the glove-based HMI. (C) Surgical training program: Photos and screenshots of the finger motions for realizing (I) mode switching, (II and III) motions of right hand, (IV) display of left hand, (V) recognition of scissors, (VI) recognition of knife, (VII) recognition of gauze, (VIII) operation of scissors (cutting), (IX) operation of knife (cutting), and (X) operation of gauze (swiping). (D) Measured triboelectric outputs from eight sensors: thumb (DD and DU), index finger (DD and DU), middle finger (DD and DU), and ring finger (DD and DU) under (i) control mode, and triboelectric outputs from 16 sensors: thumb (DD and DU), index finger (DD, MD, PD and DU), middle finger (DD, MD, and PD), ring finger (DD, MD, and PD), pinky finger (DD, MD, and PD), and palm (single electrode), under (ii) recognition mode for the motions of grabbing scissors, knife, and gauze. Photo credit: Minglu Zhu, National University of Singapore.

wearable devices. Meanwhile, even with the minimal number of sensors, the machine learning approach expands the capabilities of realizing advanced functions in human-machine interaction, i.e., realization of object recognition with an accuracy of about 96% under three layers of CNN. In the future of 5G communication and IoT (Internet of Things) applications under human-machine interaction will drastically affect the lifestyle of human in the social networking aspect, and this kind of device can improve the intelligence of machines based on the big data acquired from AI techniques. In terms of VR training programs, the augmented dual-way interaction can be achieved through the proposed glove for improving the training effectiveness. In general, this glove reveals a new possibility of being an HMI solution that is comparable to the current inertial and resistive-based gloves for the applications on VR training, entertainment, social networking, and robotic control.

MATERIALS AND METHODS

Fabrication of glove cases

Cases of fingers and palm were 3D-printed with Anycubic 4Max Pro using polylactic acid filament. The printed cases were then polished for the bonding of sensors and connected with alloy wires.

Fabrication of the elastomer-based finger sensor

A 3D-printed mold (Anycubic 4Max Pro) was prepared with three different sizes (radius: 3, 3.5, and 4 mm) of hemispheres (fig. S1). The mixture of solution A and B of Eco-flex (ratio: 1:1, model: 00-20) was poured into the mold and cured at room temperature for 90 min. Aluminum foil is diced into circles that fit the sizes of each hemisphere and bonded with wires to make the embedded electrode. The electrodes are then attached to the cured Eco-flex hemispheres and covered with additional mixture of Eco-flex. After the second curing, the fabricated elastomer sensors are released from the mold and bonded onto the inner surface of finger case by adhesive epoxy. The wires of electrodes were collected and connected to the jumper wires fixed inside the glove for routing to the microprocessor. Same approaches were applied for the sensor using PDMS (Sylgard 184, Dow Corning), with a ratio of 10:1 for the mixture of substrate and curing agent and a curing temperature at 70°C for 60 min.

Fabrication of the elastomer-based palm sensor

In fig. S2, two 3D-printed molds (Anycubic 4Max Pro) were prepared for the top dome-shaped button and the four triboelectric contact points at the bottom. The mixture of solutions A and B of Eco-flex (ratio: 1:1, model: 00-20) was poured into the mold of four contact points, and the mixture of PDMS (ratio: 10:1, Sylgard 184, Dow Corning) was poured into the mold of the top dome. After curing, the top dome-shaped button was released and placed on the top of the cured four contact points. The additional mixture of PDMS was then poured on the two parts to bond them together. After the second curing, the entire unit was released from the mold.

A holder of four bottom electrode pads was 3D-printed (Anycubic 4Max Pro). A round-shaped aluminum foil was diced into four quadrants and bonded with wires and attached to the holder.

Fabrication of the PZT chip

In fig. S3, the 1.5 cm–by–1.5 cm PZT ceramic (Fuji Ceramics Incorporation, C-6) and the 50- μ m beryllium copper foil were

polished at first. After sputtering of Cr/Au (Cr: 20 nm, 100 W, 2 min; Au: 200 nm, 100 W, 5 min) as the bottom electrode on one side (bottom surface) of PZT, it is bonded with copper foil by conductive silver paste and baked in vacuum oven (3.5 hours at 175°C). Then, the bonded PZT chip was thinned down to 20 μ m by chemical mechanical polishing. The top Au electrode was then sputtered with the same approach. After that, the as-fabricated thin PZT chip was further diced into the size of 8 mm by 5 mm by laser cutting. The wires were then connected to both top and bottom electrodes using silver paste and followed by the encapsulation of PZT chip using polyimide tape (3M).

Characterization of triboelectric and piezoelectric output

For both triboelectric sensors (finger and palm) and PZT chip, the output voltages were measured with an oscilloscope (Agilent, InfiniiVision, DSO-X 3034A). Calibrations of output voltage against force for triboelectric sensors were conducted by force gauge (Mecmesin, MultiTest 2.5-i) with a speed of 900 mm/min.

SUPPLEMENTARY MATERIALS

Supplementary material for this article is available at http://advances.sciencemag.org/cgi/ content/full/6/19/eaaz8693/DC1

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Haptic-feedback smart glove as a creative human-machine interface (HMI) for virtual/augmented reality applications

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