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Supplementary Materials for

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

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Texts S1 to S3 Figs. S1 to S8 Tables S1 and S2

Other Supplementary Material for this manuscript includes the following:

(available at advances.sciencemag.org/cgi/content/full/6/19/eaaz8693/DC1)

Movies S1 to S5



Fig. S1. (A) Schematics and (B) photos of fabrication process of elastomer based triboelectric finger sensor. Photo credit: Minglu Zhu, National University of Singapore.



Fig. S2. (A) Schematics and (B) photos of fabrication process of elastomer based triboelectric palm sensor, with backside view of top contact points, and top view of bottom aluminum electrodes. Photo credit: Minglu Zhu, National University of Singapore.



Fig. S3. Schematics of fabrication process of PZT piezoelectric actuator for haptic feedback.

Text S1. Output variations under changing humidity and long-term use

Similar to other reported devices, the proposed triboelectric sensors are also experiencing some drawbacks from external influences, such as humidity and contamination etc. As shown in Fig. S4(A), the relative humidity is controlled using humidifier to mimic the increasing of water content on the sensor surface (mainly come from environmental moisture and sweat). Owing to the elastomer material and the open structure design of glove, the rapid evaporation of water content minimizes the output degradation (15%) even at very high humidity level (90% RH), which is unlikely happened. On the other hand, the oil and dirt on skin also possess negative effect on triboelectric output after long-term use. In Fig. S4(B), the investigation of output variations against overall contamination over a certain usage was conducted. In addition, as the glove itself (except the detachable signal processing circuit) is fully washable, it is retested after we simply rinsed, washed and dried the glove. The data indicate that, although the output decays over a long-term use, it can return back to the original state after simple washing. Moreover, this kind of decay will not be observed frequently if the glove is washed routinely.



Fig. S4. (A) Output variations under changing humidity. (B) Output variations under long-term use and after rinse. Variations of triboelectric output voltage of elastomer sensor with (C) force, and (D) Strain for the elastomer-based triboelectric sensor with hemisphere shape (radius: 4 mm).



Fig. S5. FEM simulation of surface electrical potential between finger sensor and skin under (A) separation and (B)contact states.

Text S2. Customized triboelectric conditioner print circuit board (PCB) for optimizing multichannel sensing

Analog to Digital Converter (ADC) is widely adopted in various sensing applications. In most cases, the multichannel sensing is performed using single ADC and apply sequential scanning of a series of input channels, in order to saving the cost. However, in terms of simultaneous multichannel sensing, especially for triboelectric sensors, there are several constrains need to overcome for realizing real-time controlling of entire hand:

- (1) Mismatch of small triboelectric output (~100 mV) against larger measurement range of Arduino ADC (0~5V) lead to high noise level and low effective sensitivity.
- (2) Cross-talk issue, especially for those channels near the input channel, which is possibly due to coupling effect of the adjacent channels via the sampling capacitance of ADC.

To solve these issues, as illustrated in Fig. S6, through a customized triboelectric conditioner PCB, we optimize the signal readout via operational amplifier for enhancing the sensitivity, and all the channels are grounded to avoid cross-talk while maintaining the floating signal to acquire the entire triboelectric waveform. For the development boards of Arduino MEGA 2560 model, a total of 8 integrated circuits of amplifier are designed for 16 analog input channels on it.



Fig. S6. Individual signal input under multichannel reading. (A) Without triboelectric conditioner PCB attached on Arduino microprocessor. (B) With triboelectric conditioner PCB.

Text S3. Core functions in realization of virtual hand control and virtual event feedback

For haptic feedback part shown in Fig. S7(B), a reverse process of event projection can be done by applying an open source module in Unity, called Ardunity, which is specially designed for initiating mutual communication between Arduino and Unity. The collide reactor function in Ardunity offers the possibilities of transferring the virtual events into the microprocessor for enabling various responses, such as light, vibration, and voice etc. Hence, once the collide reactor recognize the interaction event, by defining the PWM operation frequency match with PZT resonant frequency in Arduino IDE, the vibrational haptic feedback can be triggered via serial communication.



Fig. S7. Illustration of the core functions for realizing (A) triboelectric sensor based virtual hand manipulation, and (B) haptic feedback from virtual events, such as collision or touching.



Fig. S8. Accuracy variation with respect to the training epoch, red curve is the training accuracy and blue curve is the validating accuracy.

No	Layer Type	No. of	Kernel/	Stride	Input Size	Output Size	Padding
		Filters	Pool Size				
1	Convolution 1	32	5	1	(None,200,16)	(None,200,32)	Same
2	Max-pooling 1		2	2	(None,200,32)	(None,100,32)	Same
3	Convolution 2	64	5	1	(None,100,32)	(None,100,64)	Same
4	Max-pooling 2		2	2	(None,100,64)	(None,50,64)	Same
5	Convolution 3	128	5	1	(None,50,64)	(None,50,128)	Same
6	Max-pooling 3		2	2	(None,50,128)	(None,25,128)	Same
7	Flatten				(None,25,128)	(None,3200)	
8	Dense (3200)				(None,3200)	(None,3200)	
9	Dense (7)				(None,3200)	(None,7)	

Table S1. The parameters for constructing Convolution Neural Network (CNN)

Classifi	cation	Penalty parameter C					
accur	acy	$1 imes 10^{-2}$	1×10^{-1}	1	10		
	100	88.02%	94.14%	93.56%	91.19%		
	200	90.84%	94.84%	95.25%	94.97%		
Linear kernel	300	91.13%	95.33%	95.89%	96.00%		
	400	91.34%	95.72%	96.26%	96.31%		
	500	91.34%	95.89%	96.41%	96.30%		
	100	63.98%	79.56%	92.66%	96.30%		
	200	58.59%	78.55%	91.43%	96.86%		
Radial basis kernel	300	53.75%	69.77%	89.23%	96.36%		
	400	51.25%	67.34%	87.03%	96.00%		
	500	50.31%	64.84%	86.22%	96.05%		

Table S2. SVM classification accuracy with different parameters and dimensions. (Remark: the data of accuracy are average values from 10 runs for each parameter)