Title

- A novel energy-motion model for continuous sEMG decoding from muscle energy to motor pattern

SUPPLEMENTARY MATERIALS

The PDF file includes:

Other Supplementary Material for this manuscript includes the following:

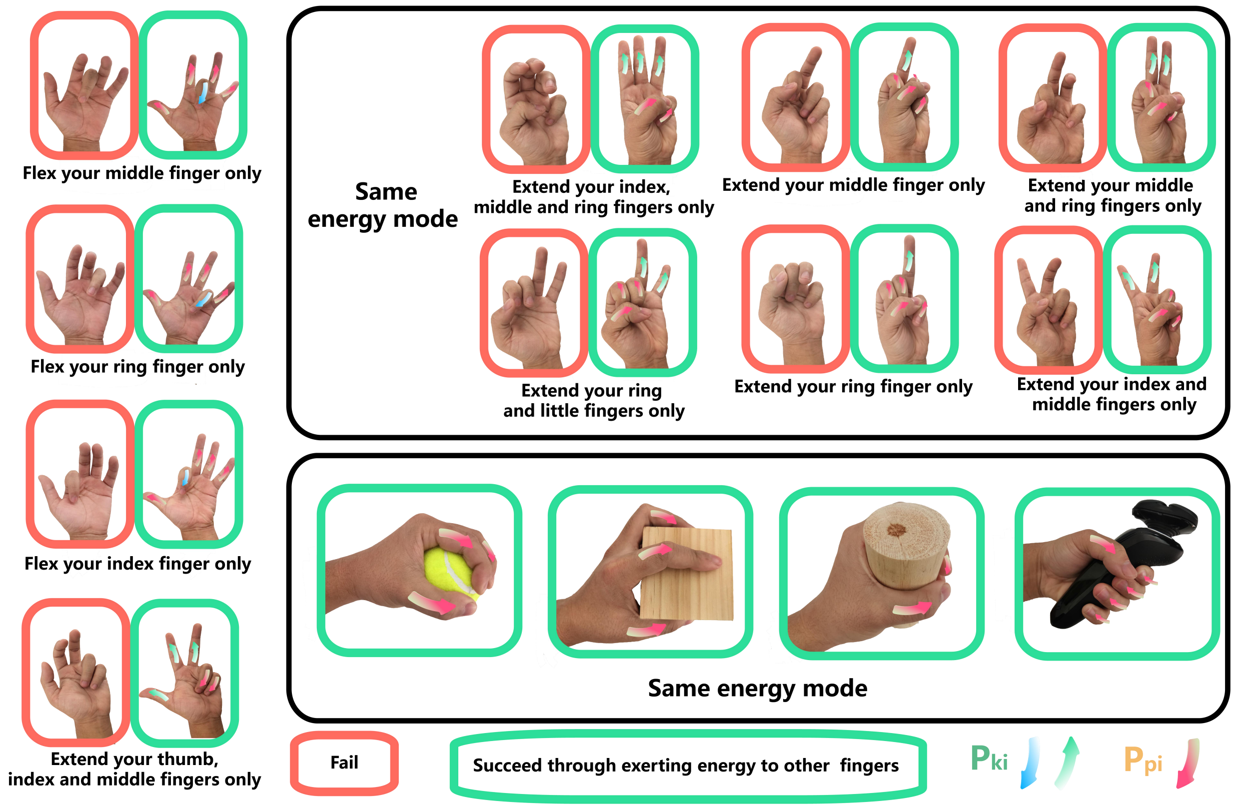

Fig. S1. The primary mechanism of human hand mimicked in the present study. We sought to regard the whole manual task as energy transfer, mimicking the adaptive mechanism of the human hand. The direction of arrows indicates "the direction of energy", and the same direction for five-fingers means that these hand motions could be achieved by the same energy mode. P_{ki} expresses the kinetic energy of the i -th finger, while P_{pi} expresses the potential energy of the i -th finger.

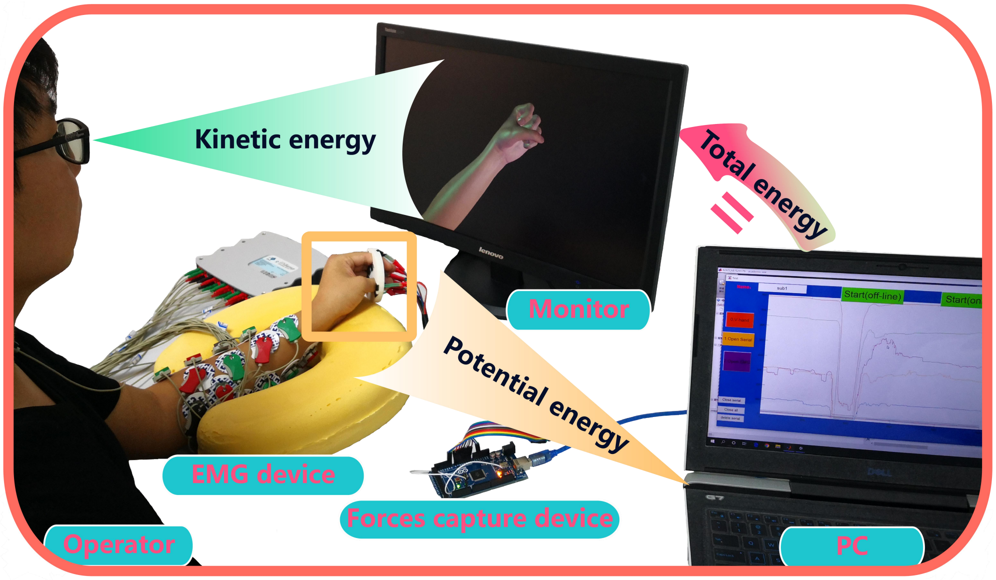

Fig. S2. Hardware structure for training states. The example of a hardware structure is composed of an EMG device, forces capture device, a PC, and a monitor. Note that, in the application, a smaller and general structure could achieve the frame of the myoelectric interface: electrodes, a microcomputer, and a motor unit.

EMG recording: Eight pairs of Ag-AgCl surface bipolar electrodes (interelectrode distance: average 3 mm) were placed on the subject's forearm to detect Surface EMG signals. Also, a single electrode was placed on the subject's to the left collarbone to serve as a ground and reference electrode. The positions of target muscles were mostly determined by palpation and the 3D-anatomical model in the experiments. The signals were sampled at 2400 Hz using four commercial 16-channel amplifiers (g.tec, Graz, Austria). Signals were band-pass filtered from 5 Hz to 500 Hz with an 8th order Chebyshev filter and a notch filter with a null frequency of 50 Hz, to ensure rejection of the 50 Hz power supply frequency. Data were recorded in MATLAB R2017b (The MathWorks, Massachusetts, USA). The software used to register the EMG signals has been programmed in Matlab Development Environment (The Mathworks Inc., Natick MA) using the API (Application Programming Interface) provided by the manufacturer (gUSBamp MATLAB API).

potential energy that converted into internal energy of the capture device proportional to forces (Finger forces recording): A fingertip force capture device that allows a simultaneous record of five-fingers forces is assembled. The capture device consists of an additional system (potential energy of each finger is converted into internal energy of the system), ten pressure sensors (RP-C7.6-LT, legact, China), and a microcontroller (Arduino Mega 2560, Arduino). The additional system was made of 3D printed polylactic acid (PLA). Ten pressure sensors were secured to each finger-hole of the additional system using tape. Specifically, each finger-hole was designed with two pressure sensors for the flexion and extension of the finger. The finger forces signals were sampled at 130 Hz and were digitized by the microcontroller with 10-bit precision. Finally, data were collected in MATLAB R2017b.

kinetic energy equaled to potential energy for each finger(Visual feedback): Visual feedback of the performed finger task was provided to the subjects using a computer graphic avatar body. The scene, displayed onto an LCD monitor, was rendered from the virtual avatar, and the monitor was positioned in order to match the subject's perspective. The movement executed by the virtual hand was flexion and extension of the five-fingers congruent with the illusory movement that was expected by the finger motions (kinetic energy) of biological hand. The visual hand was developed with the Unity 3D game engine (Unity Technologies, San Francisco, USA).

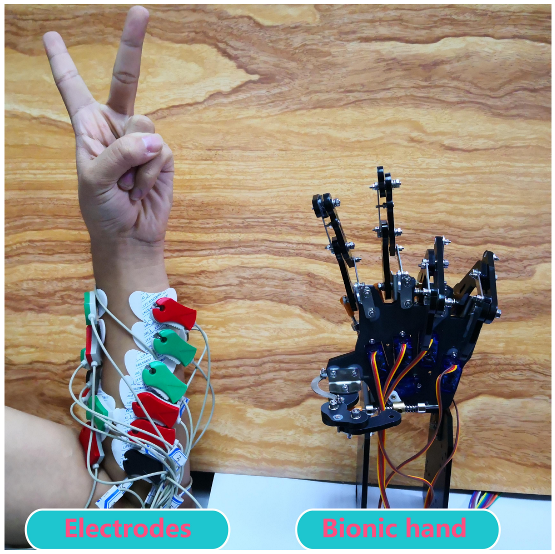

Fig. S3. Hardware structure for the application. The frame consists of electrodes, pc (in the back), and bionic hand.

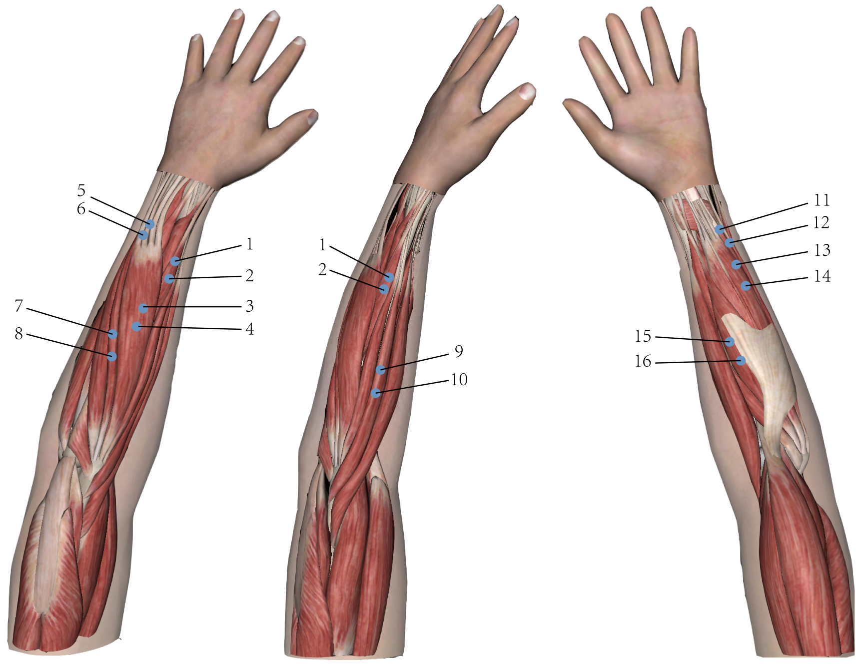

Fig. S4. EMG placement. Abductor pollicis longus (1,2): thumb abduction; Extensor digitorum (3,4): 2-5th finger extension; Extensor indicis (5,6): index finger; Extensor digiti minimi (7,8): little finger; Extensor carpi radialis longus (9,10): Wrist and thumb; Flexor digitorum profundus (11,12): 2-5th finger flexion; Flexor digitorum superficialis (13,14): 2-5th finger flexion; Flexor carpi radialis (15,16): Wrist and thumb;

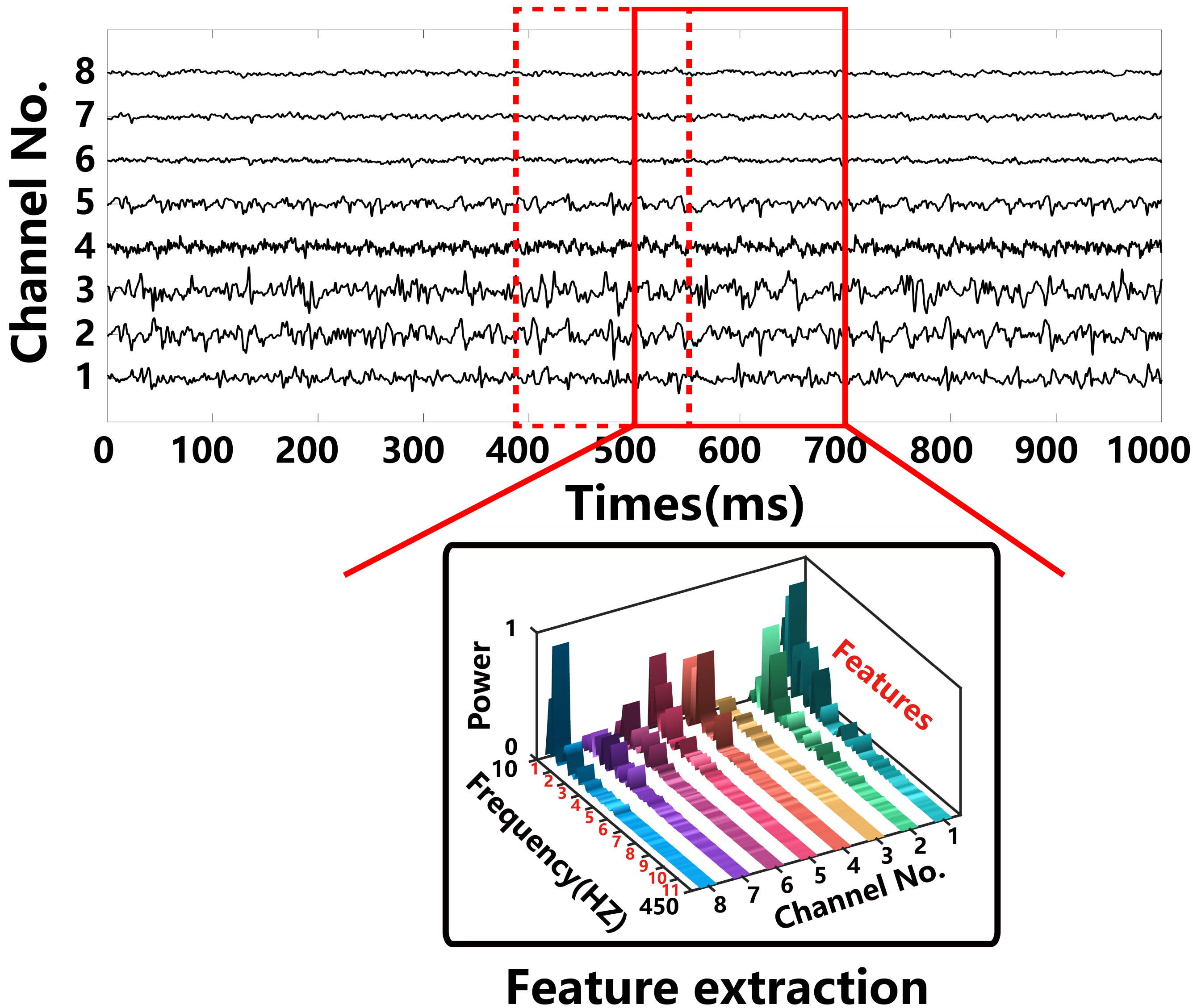

Fig. S5. Feature extraction by simple frequency-domain power. EMG amplitude is a simple and useful feature, as evidenced by commercial prostheses. To further improve the robustness to noise distinguishable by frequency band, we extract the frequency-domain power as features with a sample short-time Fourier transform, similar to amplitude in the different frequency band. Frequency bands encompassing the muscle (10–450 Hz) activities were created separately within each window. Each band was divided into 11 frequency bands (10-60HZ,60-100HZ,100-140HZ, etc.). The power across the selected frequency bands in each channel in the 200 ms sliding windows with 50 ms overlap were summed to produce 88 power features (11 features×8 channels).

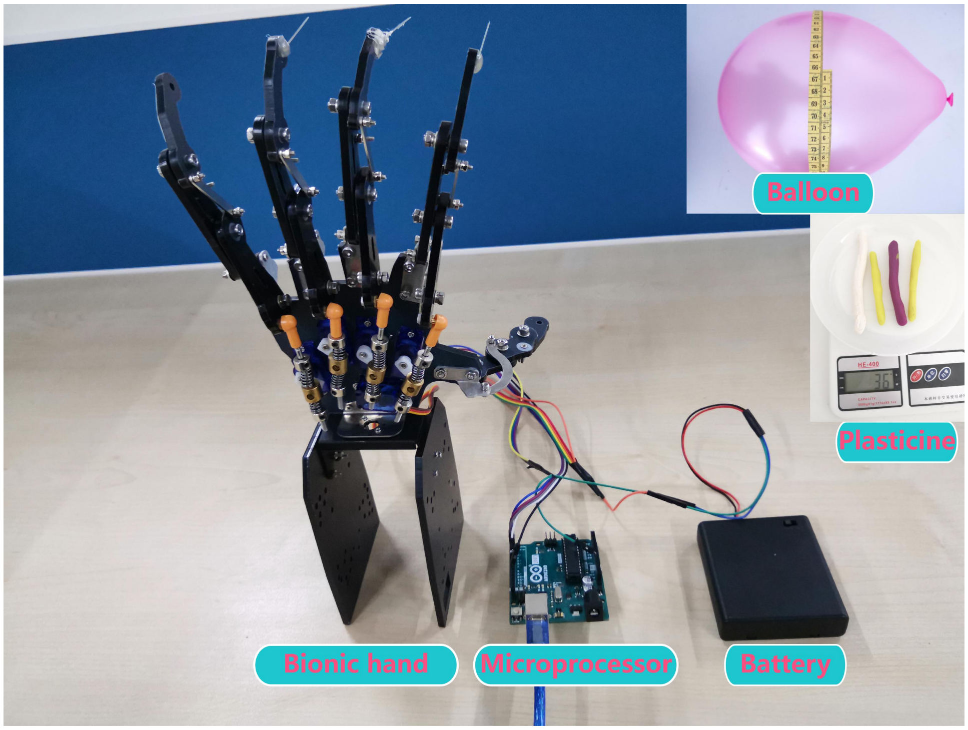

Fig. S6. Material for experiment 2 and experiment 3. Experiment 2: To test the degree to which the energy-based interface controls the amount of finger energy, we had the participant repeatedly perform these selected hand motions by controlling a bionic hand whose fingertips were fitted with steel needles, while ensuring breaking/non-breaking the balloon. Experiment 3: To assess the degree to control the finger energy in real-time, we had the participant repeatedly punch a hole in the plasticine (~1mm thickness) attached to the fixed balloon by using single fingers, while not breaking the balloon.

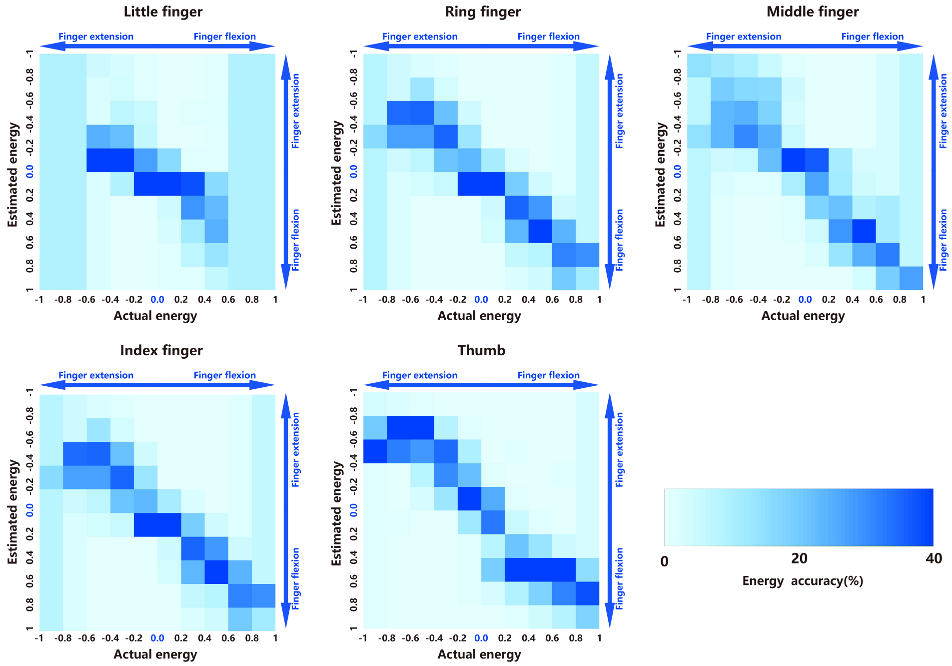

Fig. S7. Accuracy for the estimation of finger energy. Example of confusion matrix for the estimation of normalized finger energy (subject 4). Energy accuracy is defined as a ratio of the number of times within a certain energy interval to the total times. The confusion matrix shows some deviations similar to the native hand.

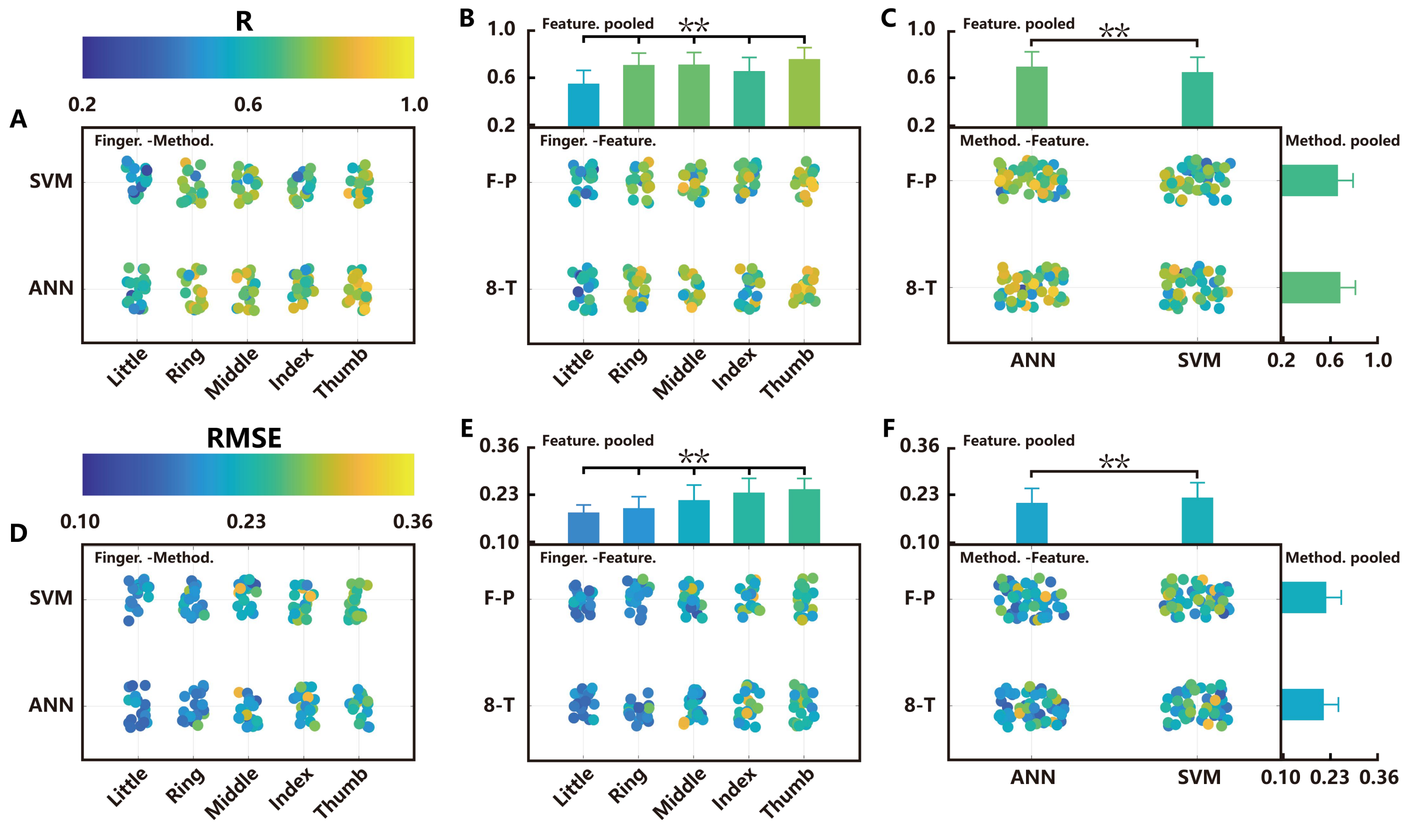

Fig. S8. The effects of features and learning methods for fingers energy. In order to assess which combination of features and learning methods could apply to the energy-based interface, a ten-fold cross-validation procedure was used to evaluate the overall statistical performance of both different features (E-T and F-P) and learning methods (ANN and SVM). We showed the result from the three-way analysis of variance (features, methods, and fingers) in the total variation (R; A, B, and C) and the total residual error (RMSE; E, F, and G). Each small colored dots represent one test of energy estimation. **P< 0.01. Data show means ± SD.

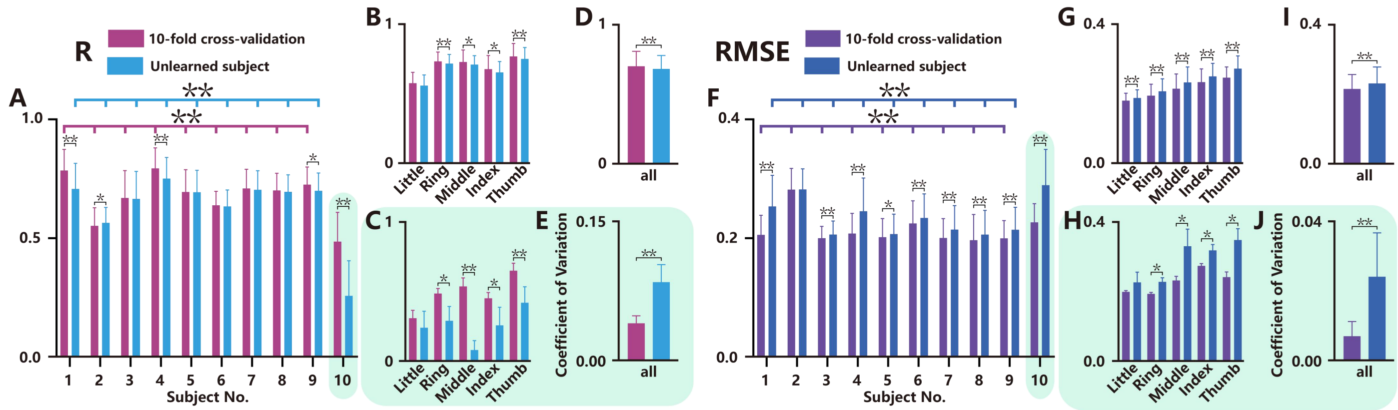

Fig. S9. The generalization of across subjects. To assess the degree to whether the energy-based interface applies to unlearned subjects, we used another ten-fold cross-validation procedure whose testing datasets from one subject totally while training datasets from other subjects, relative to the previous test. **(A)** Total variation (R) across subjects. **(B)** Total variation for single fingers (subject 1-9). **(C)** Total variation for single fingers (subject 10). **(D)** Total variation across all fingers (subject 1-9). **(E)** coefficient of variation of the total variation across all fingers (subject 10). **(F)** Total residual error (RMSE) across subjects. **(G)** Total residual error for single fingers (subject 1-9). **(H)** Total residual error for single fingers (subject 10). **(I)** Total residual error across all fingers (subject 1-9). **(J)** coefficient of variation of total residual error across all fingers (subject 10). *P< 0.05, **P< 0.01. Data show means ± SD.

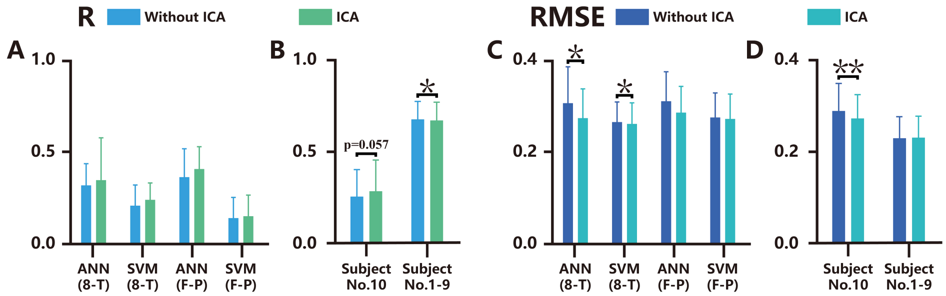

Fig. S10. Comparison of the models with ICA or without. To further assess whether the ICA model trained with the standard data applies to the subject contaminated with noise, we rebuilt a model using the synergy matrix decomposed by standard data from subject 1-9. Also, the model evaluation was accomplished through 10-fold cross-validation whose datasets divided by subjects. **(A)** Total variation (R) across conditions. **(B)** Total variation across all conditions. **(C)** Total residual error (RMSE) across conditions. **(D)** Total residual error across all conditions. *$P < 0.05$, **$P < 0.01$. Data show means ± SD.

Table 1. Experiment 1: the expression of unlearned continuous hand motions. To test the expression of multiple hand motions based on fundamental energy mode, we had the participant repeatedly sequential perform these randomly selected hand motions as faster as possible (repeated 5 times under each condition).

Hand	ICA	Subject \Completion time (s)					
		S5	S6	S7	S8	S9	S10
Trained hand (left hand)	Without ICA	90.40	80.62	90.70	85.82	96.69	102.78
		79.57	73.56	91.63	72.34	88.63	82.87
		80.76	78.10	75.67	67.52	69.45	78.17
		81.55	67.80	88.61	61.26	81.92	81.16
		75.30	63.65	82.37	66.52	66.30	69.58
	With ICA	93.27	81.14	83.44	76.02	89.81	82.25
		88.78	66.35	82.99	74.71	96.77	78.25
		76.30	72.91	91.52	73.98	88.86	77.65
		81.90	63.67	68.26	81.96	87.72	81.11
		73.22	71.30	82.30	67.32	72.13	70.24
Untrained hand (right hand)	Without ICA	89.90	89.66	87.80	66.87	88.96	411.61
		81.47	81.39	79.94	89.19	100.86	-
		80.90	75.55	102.27	77.94	79.76	-
		76.72	67.00	67.94	72.31	71.19	-
		71.84	71.41	102.27	59.76	69.64	-
	With ICA	85.48	88.34	71.99	79.30	103.04	84.79
		90.77	76.02	83.19	93.24	85.67	80.35
		79.66	72.34	83.60	79.25	76.95	82.82
		84.13	67.52	94.13	81.48	83.94	63.60
		76.23	62.26	87.20	73.90	89.26	67.07

Table 2. Experiment 2: the amount of single finger energy. To test the degree to the energy-based interface controls the amount of finger energy, we had the participant repeatedly perform these selected hand motions by controlling a bionic hand whose fingertips were fitted with steel needles while ensuring breaking/non-breaking the balloon (repeated 10 times under each condition; subject 5-9).

Hand	Balloon	Finger	Subject \Success times				
			S5	S6	S7	S8	S9
Trained hand (left hand)	Non-break	Index finger	7	8	9	9	10
		Middle finger	8	7	8	6	7
		Ring finger	9	10	7	10	8
		Middle-ring finger	9	9	8	9	7
		Index-middle finger	8	10	9	8	8
	Break	Index finger	6	8	9	7	6
		Middle finger	6	7	8	7	8
		Ring finger	8	7	6	8	5
		Middle-ring finger	8	8	8	8	7
		Index-middle finger	7	8	9	9	9
Untrained hand (right hand)	Non-break	Index finger	6	8	10	9	7
		Middle finger	7	8	9	7	9
		Ring finger	7	10	9	8	7
		Middle-ring finger	7	10	9	9	8
		Index-middle finger	7	9	8	7	10
	Break	Index finger	6	7	8	8	7
		Middle finger	7	6	7	7	7
		Ring finger	7	8	6	6	6
		Middle-ring finger	8	7	8	8	6
		Index-middle finger	9	8	8	7	7

Table 3. Experiment 3: the control of single finger energy in real-time. To assess the degree to control the finger energy in real-time, we had the participant repeatedly punch a hole in the plasticine (~1mm thickness) attached to the fixed balloon by using single fingers, while not breaking the balloon (repeated 10 times under each condition; subject 5-9).

Hand	Finger	Subject \Success times				
		S5	S6	S7	S8	S9
Trained hand (left hand)	Index finger	10	10	9	10	10
	Middle finger	10	10	10	9	10
	Ring finger	10	9	10	10	10
Untrained hand (right hand)	Index finger	10	10	10	10	10
	Middle finger	9	10	9	10	10
	Ring finger	10	10	10	10	8