# HCMG: Human-Capacitance based Micro Gesture for VR/AR

Yu Lu
yulu01@sjtu.edu.cn
Shanghai Jiao Tong University
Shanghai, China

Dian Ding*
dingdian94@sjtu.edu.cn
Shanghai Jiao Tong University
Shanghai, China

Ran Wang
wang_r@sjtu.edu.cn
Shanghai Jiao Tong University
Shanghai, China

Guangtao Xue
gt_xue@sjtu.edu.cn
Shanghai Jiao Tong University
Shanghai, China

## Abstract

Hand-tracking technology is a pivotal input method in augmented and virtual reality environments, providing enhanced interaction accuracy through micro-gesture recognition. This allows users to control devices with minimal knuckle movements, ensuring privacy and accessibility for individuals with mobility impairments. Building on the foundation of human capacitance, this paper introduces a novel approach termed human capacitance-based micro gesture (HCMG) recognition. This system employs capacitive sensors integrated within the inner lining of a wrist guard, capable of detecting subtle changes in skin-to-electrode contact caused by finger joint movements. Our approach leverages the inherent properties of human capacitance to facilitate accurate and efficient micro-gesture recognition. HCMG achieves recognition of five common micro gestures with an accuracy of 95.0%, providing a promising solution to address the limitations of existing techniques.

## CCS Concepts

• **Human-centered computing → Ubiquitous and mobile computing**.

## Keywords

Micro Gesture; Human Capacitance

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## 1 Introduction

**Motivation:** Hand-tracking technology provides a convenient input mode for augmented and virtual reality [19]. On this basis,

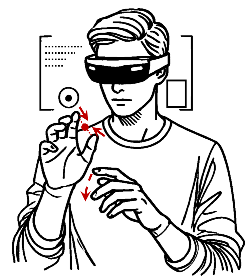

**Figure 1: Micro gesture for VR/AR system.**

micro-gesture recognition further enhances the perception accuracy of the interaction system, allowing users to interact with the device with only a slight movement of their knuckles [12]. This protects the user's privacy during the interaction process and provides a convenient interaction solution for people with mobility impairments [16].

Vision-based systems rely on cameras for unobstructed and close-up shots of the hand, and most are deployed on heads-up display devices [1, 2, 12]. However, headset devices lack comfort, and image processing requires high hardware performance. To sense the weak movement of fingers to identify gestures or sign language, inertial sensor-based solutions need to wear rings on multiple fingers, which is inconvenient [24, 25]. In addition, wireless signals such as WiFi make capturing micro-gestures in space over long distances difficult, and millimeter wave sensors in devices such as bracelets are expensive and difficult to popularise [21].

Inspired by research based on human capacitance, recent researches [7, 8, 13, 14, 22] verified that capacitive sensors can sense weak differences in touch strength, orientation, and other factors. In this paper, we propose a human capacitance-based micro gesture, HCMG. the system deploys the sensing electrodes of the capacitance sensors on the inner side of the wrist guard to measure the human capacitance, and the movement of the finger joints causes a slight change of the skin-to-electrode contact at the wrist, which enables the perception of the micro gesture.

**Challenges:** When there is even a slight change in the contact between the hand's skin and the electrode, the human body capacitance signal measured by the sensor will also vary. By processing this capacitance signal, the corresponding micro gestures can be identified. However, due to environmental electric field interference, the capacitance signal is susceptible to high-frequency noise.

*Dian Ding is the corresponding author.


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Additionally, a specific recognition model is needed to accurately map the capacitance signals generated by different micro gestures to their respective micro-actions.

**Our approach:** We develop a prototype of HCMG by strategically placing 4 ultra-miniature electrodes on the inner side of the wrist guard. The electrode and capacitance sensors are connected to collect human capacitance signals, with a Gaussian filter employed to mitigate high-frequency noise. Subsequently, a neural network-based recognition model maps the processed capacitance signals to their corresponding micro gesture labels, thereby accurately obtaining the user's micro gesture information. To validate the effectiveness of the proposed HCMG, we conduct evaluation experiments. The experimental results confirm the high efficacy of HCMG in facilitating user micro gestures. Specifically, the system achieves a high recognition accuracy of 95.0%. The contributions of this research are detailed below:

- We propose a novel interaction system, called HCMG, demonstrating the practicality of distinguishing micro gestures by employing a model of human capacitance. Our system's robustness permits accurate micro gesture recognition, paving the way for innovative wearable technologies.
- For micro gesture recognition, we employ Bi-bidirectional LSTM network architectures to analyze the human capacitance signals.
- We implement the prototype of HCMG and conduct extensive experiments in real-world environments to assess its recognition capability. The results indicate that HCMG is an innovative interaction system, and can be deployed on wearable devices to recognize the micro gestures.

## 2 Related Work

### 2.1 Micro Gesture

Micro gestures have proven useful for interaction with ubiquitous computing systems. BikeGesture [20] designed customized gloves that recognize different gestures during the user's ride based on accelerometer signals. Pucihar [21] recognized Thumb, Scratch, Tickle, and Swipe gestures using radar sensors deployed on the wrist for augmenting arbitrary physical objects. Grasping Microgesture [19] analyzed 6 common grasping styles and 12 handheld objects to investigate the influence of handles and objects on the gestures conceived by the user. STMG [12] utilized the skeletal tracking technology on the headset to extract the slightest movement of a finger, underpinning thumb-based micro-gesture interactions.

### 2.2 Human Capacitance based Interaction

Capacitive touchscreens are commonly configured in mobile devices such as smartphones and watches, and researches have demonstrated the ability of capacitive sensors to enable rich interactions. Recognizing different fingers based on human capacitance [7, 8, 13] provides a new dimension for human-computer interaction systems for mobile devices. Different parts of the finger (e.g., finger belly, fingernail) have different electrical properties [10, 15], which capacitive sensors can capture and recognize. Touchscreen-based finger angle estimation provides a slight movement in 3D space [14, 22]. In addition, human capacitance can be used as a carrier of electrical signals [4] to tap into user biometrics [5, 23].

## 3 System Framework

### 3.1 Human Capacitance

HCI systems based on human capacitance recognize interaction contents utilizing different signal patterns of human capacitance. The system measures the human capacitance at the wrist. Human capacitance can be divided into the intrinsic part and the extrinsic part. The intrinsic part is the body tissue; the extrinsic part consists of the body or electrodes and the external ground plane [17]. The intrinsic part is usually considered to be static and related to the electrical properties of the body, and the equivalent capacitance of the body part tissue is only related to the size of the part being measured. The capacitance of the tissue $C_{tissue}$ can be written as:

$$C_{tissue} = \varepsilon A/L \tag{1}$$

$$R_{tissue} = L/\sigma A \tag{2}$$

where $A$ represents cross-sectional area of the tissue, $L$ represents the length, $\varepsilon$ and $\sigma$ represents the relative permittivity and conductivity. The external part depends mainly on the external environment, such as objects in the return path (i.e., air), the contact between the electrodes and the skin, etc.

Therefore, human capacitance is usually stable with constant skin-to-electrode contact. While electrical appliances in the environment generate high-frequency electromagnetic interference based on the human body antenna effect captured by the system, the system is suppressed by Gaussian filter [23]. However, the muscle movements generated by the micro gestures can drive the skin at the wrist to move slightly, thus affecting the contact with the electrodes as shown in Fig. 3. As shown in Fig. 6, the HCMG system integrates four electrodes connected to capacitive sensors within the interior of the wrist guard to measure the corresponding changes in capacitive signals. These signals are then utilized to accurately recognize user micro gestures.

### 3.2 Signal Acquisition

As shown in Fig. 4, We utilize capacitive sensor unit [11] for the acquisition of human capacitance signals. Upon contact with the electrode pads positioned on the interior of the wrist guard, the capacitive sensor serially connects the human body capacitance with the integrated capacitor $C_1$ [18], which is subsequently connected to the operational amplifier circuit.

We define the capacitance to be measured as $C_e$, where:

$$C_e = \frac{C_1 C_{human}}{C_1 + C_{human}} \tag{3}$$

Upon receiving an excitation signal with an amplitude of $V_e$(typically an AC signal in the form of a square wave or sinusoidal wave), the stored charge $Q$ in the capacitance $C_e$ also varies accordingly:

$$\delta Q = C_e V_e \tag{4}$$

Subsequently, the capacitance $C_e$ is determined by analyzing the output voltage $V_{out}$:

$$\delta Q = C_f (V_{out} - V_f) \tag{5}$$

where $C_f$ is the feedback capacitance and $Vf$ refers to the non-inverting input voltage of operational amplifier.

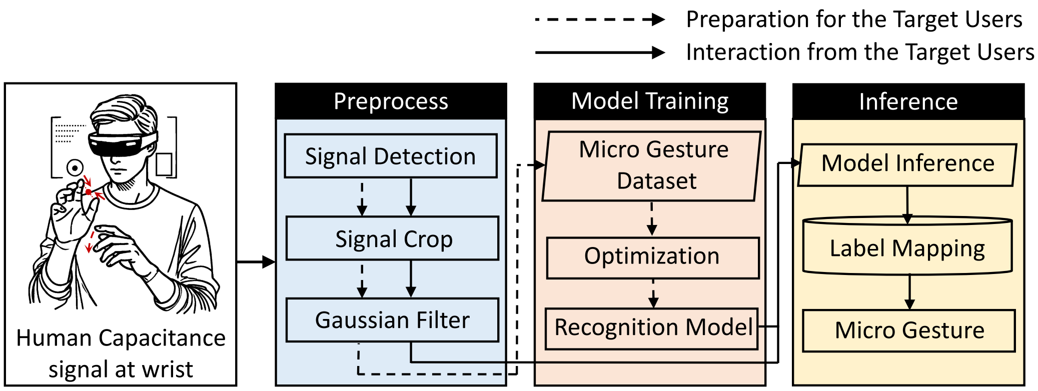


**Figure 2: The interaction system architecture of HCMG.**

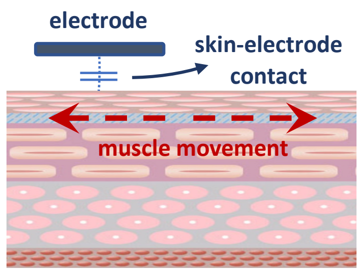


**Figure 3: Changes in skin-electrode contact induced by muscle movement.**

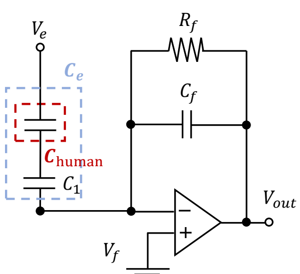


**Figure 4: Human capacitance measurement with the capacitive sensor.**

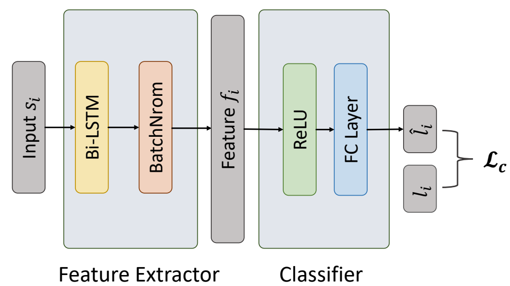


**Figure 5: Architecture of our recognition neural network.**

## 3.3 Recognition Model

Different micro gestures correspond to distinct sequences of capacitive signals, which are then identified by a neural network-based recognition model utilizing these capacitive signals. As shown in Fig. 5, the network tasks a 4-channel human capacitance signal sequence of length $L_s$ as input, and outputs an $L$-dimensional vector $\hat{l}_i$ corresponding to the $L$ possible labels.

We detail each network module of our architecture as follows.

*Feature Extractor.* For the input sequence $s_i$, we first use a bidirectional long short-term memory (LSTM) [9] to find and exploit long-range dependencies in the data. The number of features in the hidden state is 128, and the number of layers is 2. Next, after the *BatchNorm* layers, we can obtain the features $f_i$ extracted from the sequence $s_i$.

*Classifier.* The classifier is a network consisting of a *RELU* block and a fully connected layer. After the *RELU* block, the fully connected layer with modules of the form $Linear - ReLU$ outputs the possibility $\hat{l}_i$ that the sequence belongs to each label. Specifically, the layer is a Multilayer Perceptron with one hidden layer with 1024 units and an output layer with the same number of units as labels.

*Optimization.* We define the label prediction loss $\mathcal{L}_c(\hat{l}_i, l_i)$ by the *CrossEntropy* loss and train our model with $\mathcal{L}_c$.

## 4 Evaluation

As shown in Fig. 6, the HCMG system consists of a capacitance sensor (TI FDC2214 [6] with the excitation frequency of 10$MHz$) and an STM32 microcontroller (sampling rate of 30$Hz$), where the capacitance sensor is used to measure the human capacitance in real-time. The capacitive sensor is the mutual capacitance sensor and the sensor operates in shunt mode (passive sensing). The circuit's operational parameters, with a voltage range of 2.7V to 3.1V and a current of 2.1mA, lie well below the established safety thresholds of 10V for continuous contact and 20mA for human body communication [3], affirming the exceptional safety of the HCMG system. The software part is the sampling of the sensor output using the STM32, the processing, and the recognition of the sensor data on the PC side (Lenovo LEGION Y7000).

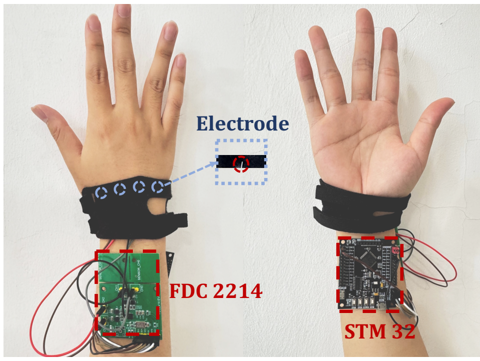


**Figure 6: Experimental setup of HCMG.**

The system acquires the human capacitance signal from the electrode pads on the inner lining of a wrist guard. The user makes different micro-gestures through finger movements.

*Dataset.* We recruited five volunteers to participate in the dataset creation process by wearing the system. Each participant performed five distinct micro gestures as shown in Fig. 7 (grab with all five fingers, rattle with the thumb, snap with the thumb, pinch with the thumb and forefinger, and click with the forefinger), repeating each micro gesture 50 times, with each repetition completed within a duration of 3 seconds. For each micro gesture, 40 repetitions were allocated to the training set, $m$ ($m$ ranging from 2 to 7) to the cross-validation set, and $10 - m$ to the test set.

*Training details.* The model was trained on one NVIDIA TESLA V100 for 50 epochs with a batch size of 16. The sequence length of each channel was limited to 90, i.e. approximately $3s$ of data sampled at a sampling rate of $30HZ$. The optimizer used is Adam with a learning rate of $1e-3$, $\beta_1 = 0.9$ and $\beta_2 = 0.999$, a weight decay of 0. A learning rate schedular is used to decay the learning rate of each parameter group by $\gamma = 0.2$ every 10 epoch.

*Micro Benchmarks.* We evaluated the recognition accuracy of HCMG for the 5 micro gestures in Fig 7. The results, illustrated in Fig. 8, show that the accuracy for the five micro gestures (grab with all five fingers, rattle with the thumb, snap with the thumb, pinch with the thumb and forefinger, and click with the forefinger) was 100%, 100%, 92%, 94%, and 100%, respectively. This demonstrates the excellent performance of our system in accurately recognizing and distinguishing between different micro gestures.

## 5 Applications

The development and application of HCMG, a human capacitance-based system for micro gesture, offer significant potential across various AR/VR applications.

**Interactive Learning and Training:** Micro-gestures can be used in educational and training applications within AR/VR environments to provide a more engaging and hands-on learning experience. For instance, medical students can perform delicate surgical simulations using precise hand gestures, offering a safe and interactive method for practicing procedures that require fine motor skills.

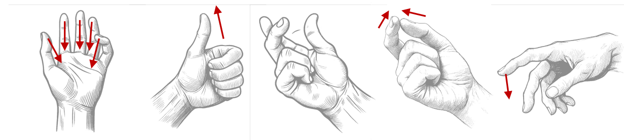

**Figure 7: Micro hand gestures of HCMG.**

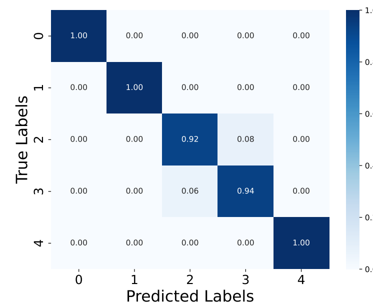


**Figure 8: Accuracy of micro gesture recognition.**

**Gaming and Entertainment:** In gaming, micro-gesture integration in AR/VR can lead to more immersive and interactive experiences. Players could use nuanced hand gestures to perform specific actions like casting spells, crafting items, or controlling game characters, adding a layer of depth and realism that enhances the overall gameplay.

**Accessible User Interfaces:** Micro-gestures can make AR/VR technologies more accessible by enabling users with limited mobility to perform gestures that are less physically demanding. This approach can broaden the usability of virtual environments, allowing a wider range of users to engage with digital content without the need for extensive physical movements.

## 6 Conclusion & Future Work

This paper has presented a human capacitance-based micro gesture (HCMG) system that leverages capacitive sensor technology to detect micro-gestures through changes in skin-to-electrode contact accurately. This system addresses several challenges associated with existing hand-tracking technologies, including the obtrusiveness of headset-based vision systems and the impracticality of inertial sensor configurations requiring multiple wearables.

Future research will focus on optimizing the sensitivity and reliability of the capacitive sensors to ensure consistent performance across diverse environmental conditions and user demographics. Additionally, integrating machine learning algorithms could enhance the system's ability to adapt to individual user gestures, thereby personalizing the interaction experience. Moreover, extending the technology to recognize a broader array of gestures and incorporating feedback mechanisms could further enrich user interactions. The ultimate goal is to pave the way for the seamless integration of micro-gesture recognition into mainstream wearable technology, opening new avenues for user-device interaction.

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