# EmoTracer: A Wearable Physiological and Psychological Monitoring System With Multi-modal Sensors

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## ABSTRACT

The monitoring of physical and mental health has been the focus of attention. At the same time, with the advancement of wearable sensors and information acquisition technology, there is no longer any satisfaction with the centralized, fixed-point traditional physiological indicator collection methods. Physiological indicator monitoring systems based on portable devices and mobile collection are gradually becoming a priority for research. Based on these needs, we present a wearable human physiological indicator monitoring system called EmoTracer. Through the self-developed and well-designed wearable collection device, body temperature, blood oxygen, heart rate and electrical skin signals are transmitted to the mobile terminal via Bluetooth communication; the mobile terminal then stores and calculates the data and displays the changes in physiological indicators in a visualized form in real-time. At the same time, we conducted an emotion recognition experiment (N=10) based on our device, which can reach an average accuracy of 91.23%, making a preliminary exploration in the direction of emotion perception.

## CCS CONCEPTS

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

## KEYWORDS

Multimodal data, Wearable computing, Body sensor, Ubiquitous computing

**ACM Reference Format:**
Danyang Wang, Jianhao Weng, Yongpan Zou, and Kaishun Wu. 2022. EmoTracer: A Wearable Physiological and Psychological Monitoring System With Multi-modal Sensors. In *Proceedings of the 2022 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp/ISWC '22 Adjunct), September 11–15, 2022, Cambridge, United Kingdom.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3544793.3560409


*UbiComp/ISWC '22 Adjunct, September 11–15, 2022, Cambridge, United Kingdom*

ACM ISBN 978-1-4503-9423-9/22/09…$15.00
https://doi.org/10.1145/3544793.3560409

## 1 INTRODUCTION

As the standard of living develops and the level of medical care enhances, human health issues are gaining wider and wider attention. For the ageing and sub-healthy population, real-time collection of their physiological indicators can effectively monitor the health status and achieve the purpose of disease prevention and early treatment. Health issues are gaining wider and wider attention as living standards develop and as medical care improves. Targeting the ageing and sub-healthy population, real-time collection of their physiological indicators can effectively monitor the state of health and achieve the purpose of disease prevention and early treatment. At the same time, the focus is gradually shifting to mental health as a major issue. The impact of depression, anxiety and other mental disorders on people cannot be ignored. In a research article published in The Lancet - Psychiatry in 2019 by Professor Huang Yueqin [10], prevalence data from the China Mental Health Survey (CMHS) was reported, which showed that the lifetime prevalence of depressive disorders in China is 6.9%, and based on that, it is estimated that there are more than 95 million people with depression in China.

In fact, with the development of artificial intelligence, there has been a lot of research on the effective monitoring of human health through sensors, which can be effectively monitored to achieve the purpose of disease prevention. There have been a lot of works on detecting depression based on electroencephalography (EEG) [4, 5, 14]. However, in the process of using these works, users have to Wear brain equipment, which is expensive and inconvenient, so it cannot be widely popularized. Moreover, there are many existing studies on sensors for monitoring health status, such as electrocardiogram (ECG) [8, 12], Galvanic Skin Response (GSR) [3, 15, 22] and photoplethysmography (PPG) [6, 20], etc. However, these studies are mainly conducted on single mode. With the high speed of computational power, there are many scholars started to research towards modalization, work [17] by data fusion of gyroscopes for multi-axis heart rate estimation and work [18] using multi-sensor modules for fall detection. In terms of emotion recognition, work [7, 9, 19, 21, 23] implements the multi-modal fusion of emotion recognition. However, it is inconvenient for users to use it, or the hardware cost is too high. In addition, some devices may require users to take the initiative to use them.

In order to make up for the shortcomings of the above research, this paper proposes a multimodal smart wearable-based human physiological data monitoring system called EmoTracer, which includes a wearable device and an intelligent terminal. The device is worn on the user's hand in a non-invasive manner to collect real-time physiological data, including heart rate signal, blood oxygen saturation signal, skin conductivity signal and skin temperature signal, and transmits the measured data to an intelligent terminal in real time via wireless transmission; In addition, the hardware development is based on commercial, low-cost sensors, and a set of portable wearable devices with integrated sensors and small size is designed on the STM32 development board independently. The device has the advantages of high sampling accuracy of each sensor, low packet loss and a rechargeable interface for multiple cycles. At the smart acquisition terminal, a mobile application is designed to pre-process the raw data from the transmitted sensors, storing, filtering and converting the signal. In turn, the human physiological data can be presented in real-time and accurately in the interface.

Compared to traditional medical and health devices, EmoTracer support long time low-power operation, and the whole system is non-invasive, convenient and comfortable, low-cost and real-time monitoring, making it more friendly for users to access. Compared to commercial electronic health products, EmoTracer has the strengths of high sampling rate and identification accuracy, and its statistics have more professional analysis value. It also combines with smart terminal applications, making it possible to facilitate the expansion of downstream data analysis tasks.

Furthermore, we have implemented a comparison test to compare the system with professional equipment to demonstrate the reliability, stability and accuracy of the system. To further extend its psychological health monitoring capabilities, we also carried out experiments on emotion recognition, which demonstrated that the data collected by the device could be used to classify emotions with a high degree of accuracy.

## 2 RELATED WORK

With the continuous popularization and iterative upgrading of wearable devices, aiming at the problems of low efficiency and low accuracy existing in traditional health measurement methods, a multi-modal health monitoring method is proposed, which mainly monitors physiological indicators such as electrocardiogram, heart rate, blood oxygen, body temperature and skin electricity. These physiological indicators have been extensively studied in health perception, and studies have found that integration of multimodal systems is expected to provide more accurate identification than unimodal systems [1].

Cai et al. [5] used the fusion of EEG multimodal data to distinguish patients with depression from normal patients, and his study showed that the fusion mode could achieve higher recognition accuracy of depression compared with single mode. Mohamed, Reham, and Moustafa Youssef [17] proposed the strategy of using gyroscope sensors on mobile phones to measure heart rate, and his study fused different gyroscope axes to achieve robust and accurate estimation. Paoli et al. [18] proposed a fall detection system for the elderly, which is a combination of wearable wireless sensor nodes based on accelerometers and static wireless non-invasive sensing infrastructure based on heterogeneous sensor nodes. The system has high reliability and sensitivity in fall detection. Miao et al. [16] used one ECG sensor and two Pulse pressure wave sensors for Simultaneous Signal collection to estimate systolic Blood pressure (SBP), mean arterial pressure (MAP), and diastolic Blood pressure (DBP). The experimental results show that the multi-sensor fusion method can show good accuracy and robustness to different populations. Li et al. [13] designed a wearable physiological monitoring system based on Wi-Fi technology, and their device integrated ECG signal sensor, temperature sensor and motion sensor. Their proposed system is capable of long-term monitoring of physiological signals. All these methods demonstrate the feasibility of multimodal fusion method

In terms of emotion recognition, Samarth Tripathi, Sarthak Tripathi and Homayoon Beigi [21] proposed the use of voice, text and action data for multimodal emotion recognition. Professor Bin Hu et al. [23] of Lanzhou University proposed a new fusion method using GBDT classifier, which used the data of two channels of two frontal EEG for emotion classification, and achieved the highest and average classification accuracy of 76.34% and 75.18% in the DEAP database [11]. Furthermore, Muhammad Adeel Asghar et al. [2] proposed the fusion of EEG multimodal data to recognize emotion, and this method achieved 77.4% accuracy in the DEAP database [11]. Huang et al. [9] proposed a multi-modal fusion emotion recognition method based on facial expression and EEG technology. EEG is mainly used to assist facial expression to achieve more reliable emotion recognition. Raheel et al. [19] used electroencephalogram (EEG), photoplethysmography (PPG) and galvanic skin response (GSR) to collect physiological signals for emotion recognition. The results show that the accuracy of emotion recognition using multimodal features is further improved than that using unimodal features.

Existing methods are either complicated to use, require expensive additional equipment, or are not accurate enough. Our method can reduce the cost of wearable devices by utilizing existing physiological information sensors, improve the portability of devices, and realize real-time recognition of users' emotional perception.

## 3 IMPLEMENTATION

The EmoTracer system consists of three parts: the physiological indicator collection device, the Android APP and the data processing.

### 3.1 Hardware Design

The wearable device includes a temperature module, a heart rate module, an skin conductivity module, a blood oxygen module, a wireless communication module and a microcontroller.

These modules convert the collected data into digital signals via the ADC on the microcontroller. The microcontroller transmits the received data to the wireless communication module at set intervals using the UART protocol, which in turn sends the data to the intelligent device via the wireless communication module. In addition, the device is provided with a wrist strap which is secured to said encapsulated housing for securing the device to the user's wrist in a non-intrusive manner. The microcontroller is an STM32F103C8T6 Cortex-M3 32bit microcontroller. The main frequency of the mi-

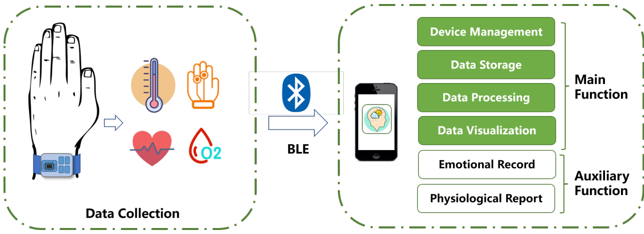


**Figure 1: Overview of the EmoTracer system: The system involves two parts: the wearable device and the terminal software. The user wears a wearable device on the wrist to collect body temperature, oxygen saturation, heart rate and skin conductivity data and transmits the data to the smart terminal via low-power Bluetooth 5.0. The smart terminal software performs the main functions of device management, data storage, data processing and data visualization as well as the auxiliary functions of psychological survey and body condition reporting.**

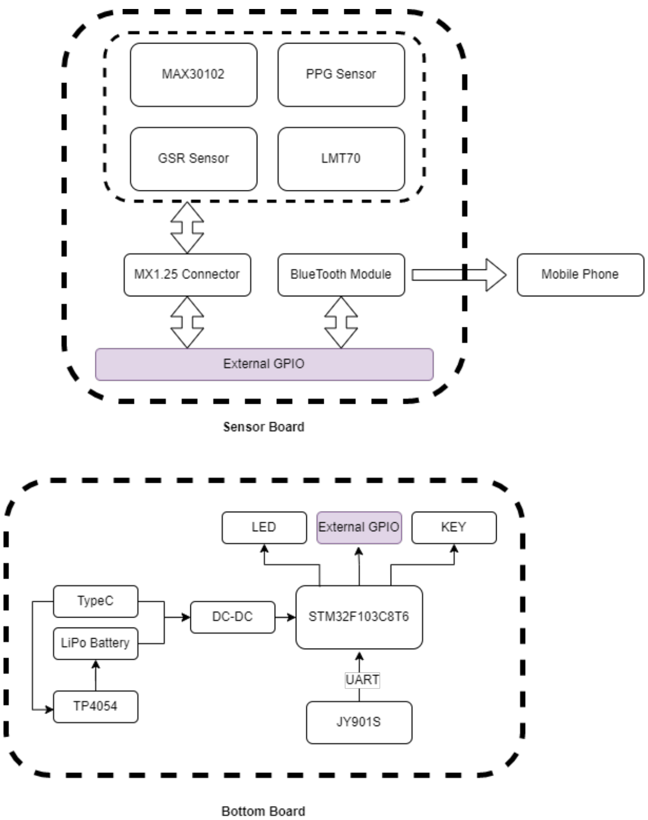


**Figure 2: Hardware board structure diagram**

crocontroller is up to 72 MHz, the power supply chip is SY8089 DC-DC buck chip with ultra-low quiescent current, the lithium battery voltage to 3.3V for the microcontroller and other sensors to use, the charging chip model TP4054 charging circuit, through the TypeC plug into the power supply can be set after the maximum

**Table 1: Configuration of each sensor**

| Signal | Sensor | Sampling Rate |
|---|---|---|
| Temperature | LMT70 | 100 Hz |
| Blood Oxygen Saturation | Max30102 | 400 Hz |
| Heart Rate | Pulse Sensor | 400 Hz |
| Skin Conductivity | Grove GSR | 200 Hz |

500ma current size to the lithium battery power supply.The type of Bluetooth module is the RF-Star EFR32BG22A1 ultra-low power Bluetooth module, which supports the BLE5.2 protocol.In addition, the MX1.25 sensor is used due to its features that allow the use of an optocoupler switch for individual control of the power supply voltage for each sensor to control power consumption; the provision of an MX1.25 sensor interface to receive physiological data signals from external sensor inputs; and the use of a low quiescent current DC-DC chip to reduce static power consumption to improve endurance. The sampling rate and data accuracy of the sensors of each acquisition module and the meaning of the acquired data are shown in Table 1. EmoTracer device uses the BLE communication

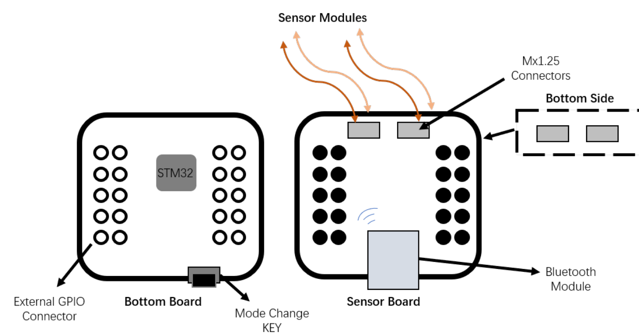


**Figure 3: Sensor circuit board layout**

protocol and the lower computer program sends data packets every 50ms. As each sensor has a different sampling rate, the oximetry module with the highest sampling rate is used for calibration and the data in the corresponding ADC data register of the sensor is read by taking the residual relationship. Once the blood oxygen module has collected 20 sets of data, the data from the different sensors are stored according to the protocol rules and sent to the Bluetooth module via the serial port.

## 3.2 Software Design

The following is the initial design and implementation of the EmoTracer mobile application.

- **Data Collection and Visualization Interface**: The interface contains the Bluetooth connection of the device and a display of the data from each sensor module (heart rate, oxygen saturation, skin temperature and skin conductivity) after connection.
- **User Information Interface**: The main function of this module is to collect personal information from users and to

carry out scale assessments, and to store the data so that subsequent doctors and researchers can make a reasonable assessment of the user's mental health status.

- **Emotion Log**: This interface is mainly used for the recording of the user's daily emotions, either by way of a log entry or a picture option, to enable a summary of the user's emotions over time.
- **Special Disease Record Interface**: Research has shown that psychological disorders such as anxiety and panic attacks are often accompanied by clinical physical symptoms. This module allows the user to record the moment of attack, the moment of recovery, the symptoms associated with the attack and to share the record with a doctor or researcher. The software combines images of various parts of the body to create a model of the human body, which can be clicked on to record the sensation of the corresponding part.

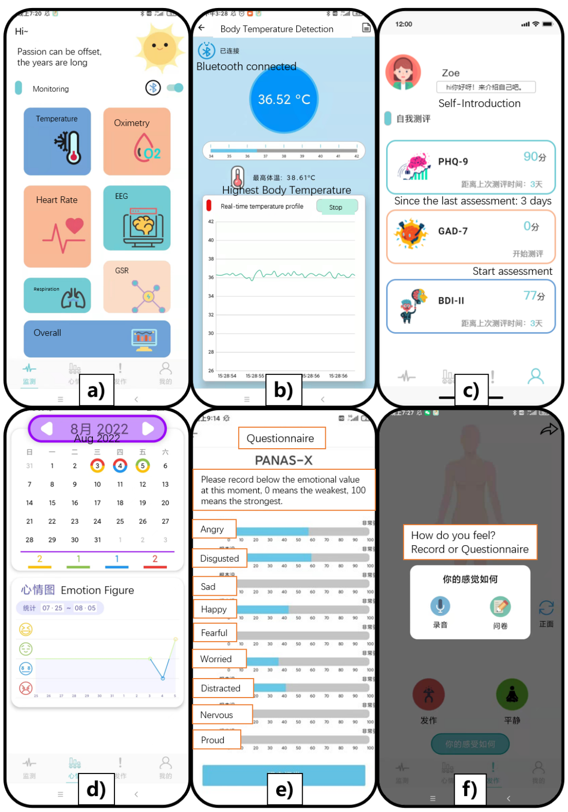


**Figure 4: EmoTracer workflow with initial UI design. a-b) Data collection and visualization interface, c) User information interface, d) Emotion Log, e-f) Special disease record interface**

## 3.3 Emotion Recognition

By performing FFT on each channel signal, the analysis showed that there existed industrial frequency interference problems, in order to reduce these industrial frequency interferences, a short-time Fourier transform is first applied to each of the resulting channels, and then the coefficients corresponding to these interfering components are set to zero signal sequence. The low-pass filter was set to a cut-off frequency of 0.3 Hz because the skin electrical signal changes slowly and the effective frequency is between 0 and 0.3 Hz. The PPG distribution is mainly at 12 Hz. For the elimination of this interference, the FFT is performed on the signal, first truncating the components below 0.5 Hz in order to retain the band from 0.1 Hz to 12 Hz. The Savgol filter was chosen for the body temperature signal. The system selected data from 10 people, each person collected valid emotional data for 15 minutes, the data was sliced according to each sensor sampling rate, the slicing window is 1s, After signal slicing, data filtering and normalization of the raw signal and data fusion, the total amount of data was 10050. While 80% of the data is used for training, 20% is used for testing and each channel used resnet18 network for emotional classification.

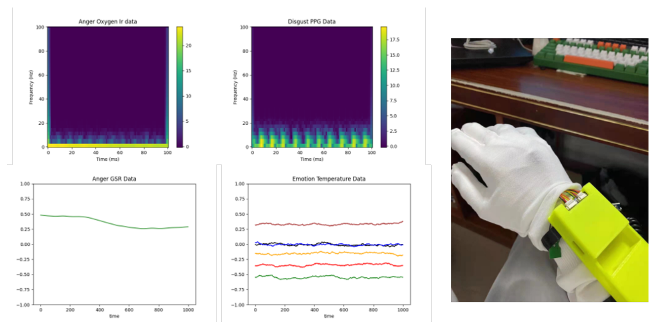

**Figure 5: Time-frequency diagram of different signals (left) and prototype of the device (right)**

## 4 EVALUATION

To verify the reliability of the data collected by our device, we compared the correlation between the EmoTracer device and the professional device Biopac MP160, as shown in Figure 6, with the x-axis indicating the two set time pairs of their data points and the y-axis indicating their correlation, which can be seen to be as high as 0.99. In addition, the oxygen saturation and heart rate module was tested against the Hear Force POD-1 model pulse oximeter with a maximum error of ±1 %. Table 2 shows a comparison of the data from the three experimenters. There was less variability in the data at rest as well as in the breath-holding state (indicated by BH in the table).

We recorded data from 10 subjects under six different emotions induced by watching an emotional video. Among the emotional stimulus materials used was the China's Standard Emotional Video Stimuli Materials Library (CEVS)[24]. The six basic emotions included neutral, happy, sad, angry, fearful, and disgusted. Each of these mood videos should be no more than 2 minutes in length, with 5 clips selected for each mood video. Each subject was exposed to all stimuli in one experiment in n sessions, and one stimulus was shown to the subject in each session. Before playing each section of stimulus material, subjects were given a buffer of 2-3 minutes to calm their mood, and this mood adjustment time could be longer until subjects had regained their composure. After each stimulus was played, subjects were asked to self-report their true emotions while

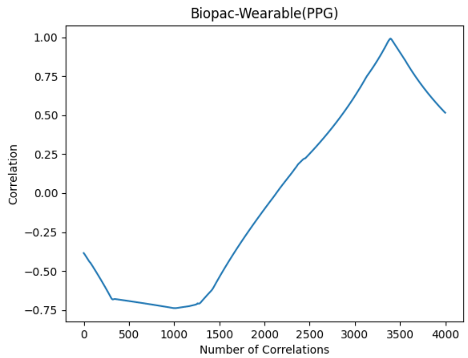


**Figure 6: EmoTracer vs Biopac comparison results**

**Table 2: EmoTracer vs Hear Force POD-1 Oxygen saturation(Unit: %) comparison results**

| Subj # | Devices | Rest 1 mim | BH 15s | BH 30s |
|---|---|---|---|---|
| Subj 1 | Ours | 100 | 99 | 97 |
| | POD-1 | 99 | 99 | 96 |
| | Variance | 1 | 0 | 1 |
| Subj 2 | Ours | 100 | 99 | 99 |
| | POD-1 | 99 | 99 | 98 |
| | Variance | 1 | 0 | 1 |
| Subj 3 | Ours | 99 | 98 | 98 |
| | POD-1 | 97 | 98 | 97 |
| | Variance | 2 | 0 | 1 |

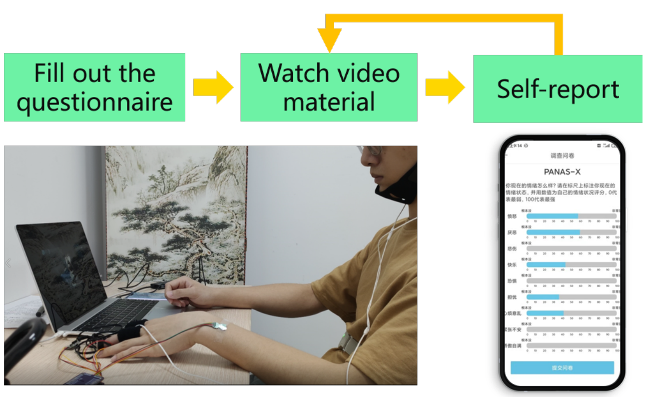


**Figure 7: Emotional experiment process**

watching the stimuli in the app. EmoTracer was used to classify the emotions under the Resnet18 model, and Figure 8 demonstrate a confusion matrix of emotion recognition for 10 subjects. On the graphic, 0 represents neutral, 1 represents sad, 2 represents happy, 3 represents angry, 4 represents disgust and 5 represents fearful. It can be seen that its average recognition accuracy for the six emotions is up to 91.23 %.

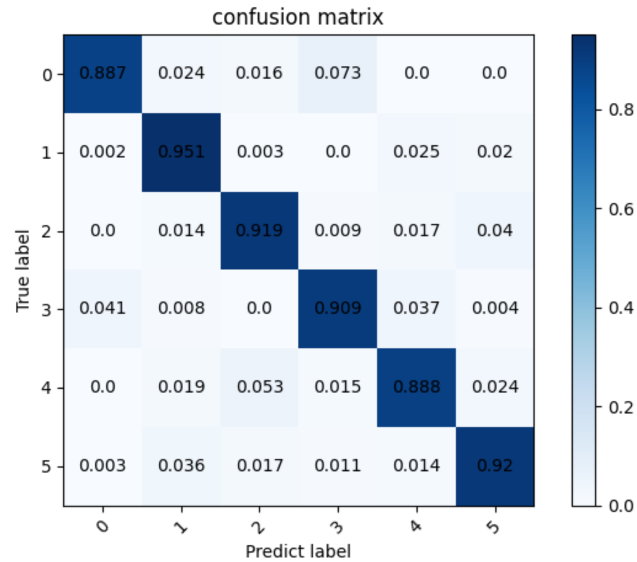


**Figure 8: Confusion matrix for emotion recognition results**

## 5 CONCLUSION & FUTURE WORK

Physical and mental health is a must for a normal study, work and life. Without a healthy physiology, one will not be able to maintain abundant energy and vigour for a long time, and will even be troubled by some diseases and will not be able to engage in normal social activities at all. Without a healthy psyche, one will often be in a bad psychological state such as anxiety, depression, isolation, low self-esteem, resentment and suspicion. The traditional medical model is unable to meet people's requirements, and people want to be able to monitor their own health status in a convenient and quick way, so the mobile medical model has become the new development trend. This paper proposes a universal, portable and low-cost wearable physical and mental health monitoring system to provide a technical implementation for mobile healthcare.

There are many areas that could be optimized and improved in this paper. The portability and durability of the hardware device could be further improved to make it more user-friendly for use in everyday life. In the meantime, additional servers could be deployed. On the basis of the current physiological information collection system, a corresponding server can be deployed and communication between the server and the client can be realized, so that a hardware-client-server communication framework can be set up to achieve real long-distance data collection and health monitoring. Furthermore, the emotion perception function can be extensible, as the current one only implements a simple emotion recognition for a small number of users, further large-scale and real-time emotion recognition can be deployed to perfect the overall system.

## ACKNOWLEDGMENTS

This research was supported in part by China NSFC Grant ( 62172286, U2001207), Guangdong NSF Grant (2022A1515011509, 2017A030312008), Shenzhen Science and Technology Foundation (ZDSYS20190902092853047, 2021ZDZX1068). Yongpan Zou is the corresponding author.

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