

BeaType: an alternative communication method based on RFID devices

Qiang Wang, Dengao Li, Shuang Xu, Xiaoxia Song, Yajun Li, Huiting Zhang, and Jumin Zhao^(✉)

Abstract Neuromuscular system diseases may lead to severe paralysis and loss of language function. Patients cannot communicate normally with the outside world and are difficult to receive timely help. To address this issue, researchers have developed various alternative communication technologies, among which breathing-based typing is a common method. However, existing technologies have limitations: some studies only support sending a small number of pre-set sentences, preventing users from freely expressing their intentions; others require interaction with a display screen and are not adaptable to blind patients. In our previous work, we developed a breathing-based alternative communication technology based on commercial Radio Frequency Identification (RFID) devices, but its typing efficiency still needed improvement. In this study, we propose the BeaType system, design fine-grained method for expressing information through breathing, develop a new breathing movement feature extraction algorithm, derive a model for identifying breathing movements using a breathing control model, and finally output binary information using the proposed decoding model. Experiments show that BeaType has stable performance, and its typing efficiency is 15% higher than that of the previous work.

Keywords RFID; Breath monitoring; Text input; Alternative communication

1 Introduction

1.1 Background

There are tens of millions of people around the world who suffer from various diseases that can cause severe paralysis and loss of language function, such as motor neuron disease^[1], stroke^[2], spinal cord injury^[3], and multiple sclerosis^[4]. Such patients urgently need alternative communication techniques to help them communicate with others. The existing alternative communication techniques can be divided into four categories: alternative communication techniques based on gesture, alternative communication techniques based on facial action, alternative communication techniques based on brain-computer interface (BCI), and alternative communication techniques based on respiration.

Alternative communication techniques based on gesture. This kind of method requires the user to express his intention by body action, such as hand gestures^[5–10], head gestures^[11–13], and neck motions^[14], etc. For example, WiMorse^[5] uses commercial Wi-Fi devices to sense the user's finger movements. The user leverages different patterns of finger movements to represent the basic symbols of Morse code. Wang et al.^[14] attach flexible strain sensors to the user's neck and extract neck movement patterns from the collected sensor data to control wheelchair movement. These methods require the user to have the ability to move their body and are not suitable for patients with severe paralysis.

Alternative communication techniques based on facial action. Some researchers have proposed to use blinking or eye movements to express intentions^[15–17]. Li et al.^[16] use electrooculogram (EOG) devices to collect users' blink data and use them to control the movement of an electric wheelchair. Wang et al.^[17] use a camera to capture the users' gaze positions and control the wheelchair's movement based on that information. However, patients with eye disease may not be able to use these techniques. Some studies utilize mouth movements to express intentions. For example, Chang et al.^[18] place surface electrodes on the the occlusal muscles of both cheeks to receive surface electromyography (sEMG) signals, and then use these signals to control a powered wheelchair. However, placing devices on the cheeks may cause discomfort to the user.

• Qiang Wang and Xiaoxia Song are with College of Computer and Network Engineering, Shanxi Datong University, Datong 037009, China. E-mail: wangqiang510@126.com; sxxly2002@163.com.

• Dengao Li is with College of Computer Science and Technology (College of Data Science), Taiyuan University of Technology, Taiyuan 030024, China, and also with Key Laboratory of Data Governance and Intelligent Decision Making of Shanxi Province, Taiyuan 030024, China. E-mail: lidengao@tyut.edu.cn.

• Shuang Xu and Huiting Zhang are with College of Artificial Intelligence, Taiyuan University of Technology, Taiyuan 030024, China. E-mail: xushuang@tyut.edu.cn; zhanghuiting@tyut.edu.cn.

• Yajun Li and Jumin Zhao are with College of Electronic Information Engineering, Taiyuan University of Technology, Taiyuan 030024, China, and also with Key Laboratory of Data Governance and Intelligent Decision Making of Shanxi Province, Taiyuan 030024, China. E-mail: liyajun9504@163.com; zhaojumin@tyut.edu.cn.

^(✉) To whom correspondence should be addressed.

Manuscript received: 2026-03-27; revised: 2026-07-29; accepted: 2026-09-16

Table 1 Scheme based on pattern expression^[23].

Label	Transit Language
Breath pattern 1	“Hello, good morning”
Breath pattern 2	“Thank you”
Breath pattern 3	“My name is ...”
Breath pattern 4	“May I have a train ticket please?”

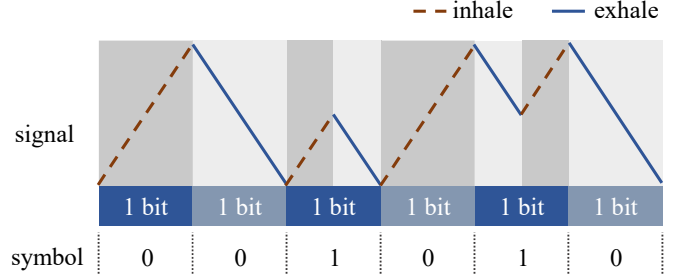
Alternative communication techniques based on BCI.

Through BCI^[19, 20], users can directly control external devices or perform text input via their thoughts. Based on device implantation methods, BCI can be categorized into non-invasive and invasive types. The former has relatively low signal resolution, while the latter may cause irreversible damage to brain tissue. In addition, BCI systems typically demand extensive training and regular calibration, significantly increasing the user burden. And the generalization ability of existing methods needs further improvement^[19, 20]. Some studies have attempted to use BCI devices to detect users’ head movements and blinking movements to control computers or operate wheelchairs^[21, 22]. However, patients with severe paralysis often cannot complete their limbs or facial movements on their own, further limiting the practical application of this kind of method.

Alternative communication techniques based on respiration. Compared with the other three types of alternative communication techniques, breath-based alternative communication techniques have natural advantages. This is because patients with severe paralysis usually have the ability to breathe on their own. The existing breath-based alternative communication techniques can be divided into two categories: pattern expression-based schemes^[23–25] and spelling-based schemes^[26, 27].

- **Pattern expression-based schemes** assign a unique breathing pattern to each text pre-stored in the system^[23–25]. As shown in Table 1, the user drives the system to output the corresponding sentence by executing a specific breathing pattern. These schemes can only output a small number of predefined sentences and can not meet the needs of users to express their intentions freely.
- **Spelling-based schemes** use breathing to select characters from the screen to complete the spelling of words^[26, 27]. These methods require users to interact with the screen and can not provide services for blind patients, so they do not have general applicability.

In our previous work, we proposed ReType^[28], adopting binary sequences to represent characters. ReType^[28] utilizes a complete breathing cycle to represent a symbol and specifies

**Fig. 1** Mapping between respiratory beat information and symbols.

that a normal breath represents ‘0’ and a deep breath represents ‘1’. In another work, we proposed ExHIBit^[29], where inhalation and exhalation correspond to distinct symbols. Due to its improved information representation, the input efficiency of ExHIBit is higher than that of ReType. However, ExHIBit uses the breath-holding action as an indicator of symbol value change ($0 \leftrightarrow 1$). The breath-holding action takes up additional time, resulting in a limited improvement in the overall input efficiency.

1.2 Our Method

Patients can adopt methods such as Hoffman code or Braille code to map characters to binary code. Then they use breathing to represent the binary code information, which we call information representation. We define exhalation/inhalation with greater depth as a “full beat” action, and exhalation/inhalation with lesser depth as a “half beat” action. Users must ensure that the depth of “full beat” exhalation/inhalation is significantly greater than that of “half beat” exhalation/inhalation. We generally require that the ratio of the “full beat” depth to the “half beat” depth be greater than τ , where $\tau = 1.4$. In other words, since $\frac{1}{\tau} = 0.7$, the depth of “half beat” must be less than 70% of the depth of “full beat”. As shown in Fig. 1, we use one “full beat” action to represent ‘0’ and two “half beat” actions to represent ‘1’. Based on this information representation method, we name this work **BeaType** (abbreviation of **Beat** and **Type**). In practical application, the user may change the breathing rate to control the input speed. Therefore, the duration of the breath action cannot be taken as a feature when identifying the breathing action label (“full beat” or “half beat”). Since the depth of the user’s breath is relatively stable, the amplitude feature can be used to identify the breathing action label.

In this paper, we leverage commercial-off-the-shelf (COTS) RFID devices to sense breathing movements. As shown in Fig. 2, we attach the RFID tag to the user’s chest and deploy the RFID reader’s antenna in front of the user. An

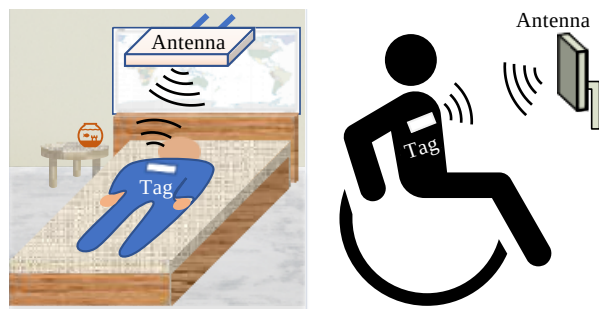


Fig. 2 Equipment deployment method^[28, 29].

RFID reader communicates with an RFID tag by transmitting wireless signals via an antenna. Following each successful communication, the RFID reader transmits information such as the RFID tag's ID number, phase value and timestamp to the host computer. The RFID reader continuously communicates with the RFID tag, thereby obtaining the time series of the phase or referred to as "phase signal". Let d represent the straight-line distance between RFID tag and RFID reader's antenna. The phase value is directly related to d . As the RFID tag is affixed to the user's chest, the value of d changes in response to the rise and fall of the chest during breathing, thereby causing the phase value output by the reader to vary. This is the theoretical basis for using RFID equipment to collect respiratory signals. When inhaling, the phase signal shows an increasing trend; when exhaling, the phase signal shows a decreasing trend.

We proposed a signal feature extraction method based on recursive processing to extract fine-grained respiratory action features from respiratory signals. Subsequently, a breathing control model is utilized to obtain the labels of the respiratory actions. We use one "full beat" action to represent '0' and two "half beat" actions to represent '1'. Therefore, the obtained breathing action labels and symbols cannot be matched one-to-one. To address this issue, we further proposed a decoding method based on recursive processing.

1.3 Advantages of BeaType over Prior Art

The advantages are mainly reflected in the following four aspects.

- Traditional methods only allow users to express predefined sentences, and the number of predefined sentences is small^[23–25]. BeaType uses breath to represent binary symbols, allowing users to freely express intentions.
- Compared to ExHIBit^[29], BeaType achieves approximately a 15% improvement in input efficiency.
- Our method achieves real-time detection of fine-grained respiratory information through recursive processing,

eliminating the need to store historical data. This facilitates the reduction of hardware configuration and reduce costs during future commercial promotion.

- BeaType is training-free. Therefore, there is no need to collect training data, which can reduce user costs.

1.4 Challenges and Solutions

We face four challenges.

- The communication between the RFID reader and the RFID tag follows the frame time slot Aloha protocol^[28], so the phase signals collected are non-uniformly sampled. Traditional methods usually require resampling the signals to restore them to uniform sampling signals, but this batch processing method reduces the real-time performance of the system.
- We use fine-grained breathing movements to represent symbols. If the de-noise effect is excessively pursued to obtain a smooth phase signal, the fluctuation characteristics of the respiratory signal will be lost, resulting in failure to decode. In order to avoid this problem, noise is still retained in the preprocessed phase signal, but this makes subsequent signal feature extraction difficult.
- The lack of a unified time reference when patients transmit information through breathing makes the duration of each exhalation or inhalation unstable. In addition, in practical tests, patients may suddenly change their breathing rate, further exacerbating the instability of breathing duration. Therefore, the signal processing method used is required to be more robust to changes in respiratory rate.
- Our previous research has shown that users' breathing amplitude has short-term stability, and there may be significant differences in the amplitude between two breaths spaced apart^[28]. In other words, breathing amplitude presents instability over the long term, which poses challenges to the recognition of breathing movements.

In order to solve the above problems, our system is designed based on the recursive processing concept, which is not sensitive to whether the signal is sampled uniformly and has real-time processing capabilities. The system has good robustness against noise in the preprocessed signal, enabling the preprocessed data to effectively retain the characteristics of respiratory movements. In response to the phenomenon of unstable user respiratory rates, we only extract the amplitude features of breathing as the basis for action recognition. Further, to tackle the challenge of unstable respiratory amplitude over a long-term perspective, we introduce a breathing control model and derive a breathing action label recognition model

based on recursive processing. This model essentially uses the amplitude information of adjacent respiratory actions to identify the type of respiratory actions, thereby indirectly solving the problem caused by unstable respiratory amplitude. At the same time, our method is also insensitive to changes in respiratory rates.

1.5 Results and Contributions

We have implemented BeaType based on commercial RFID devices, enabling severely paralyzed patients to freely express their intentions through breathing movements. Nursing staff can promptly understand the patients' needs through this method, thereby providing them with more adequate care and allowing them to live with greater dignity. Experimental results show that BeaType exhibits excellent robustness in various experimental scenarios, and its input efficiency has increased by 15% compared to existing method. Additionally, during the system implementation process, we propose new signal processing methods, which can be widely applied to the feature detection and extraction of signal waveforms in other fields.

The rest of this paper is organized as follows. Section 2 gives a detailed description of our method. Experiments and analysis are reported in Section 3. Section 4 introduces the impact of key parameters. We conclude in Section 5.

2 BeaType System

2.1 Preprocessing

We use commercial RFID devices to collect respiratory signals. When the distance between the RFID tag and the RFID reader is near the integer multiple of half the carrier wavelength, the phase signal is prone to "phase wrapping", that is, the phase signal is discontinuous^[28]. Therefore, the continuous phase signal is first restored by the recursive phase unwrapping algorithm^[30]. Then EWMA filter^[31] is used to suppress the noise in the phase signal. If we pursue the smoothness of the signal too much, the beat characteristics of the useful signal will be severely attenuated which will have a negative effect on decoding. Therefore, the preprocessed signal still contains a certain amount of noise.

2.2 Feature Extraction

The amplitude of the preprocessed phase signal shows an increasing trend during inhalation, referred to as "up-trend" (UT). The starting point (the trough of the signal) and the end point (the peak of the signal) of UT correspond to the beginning and end of inhalation, respectively. The amplitude of the preprocessed phase signal shows a decreasing trend during

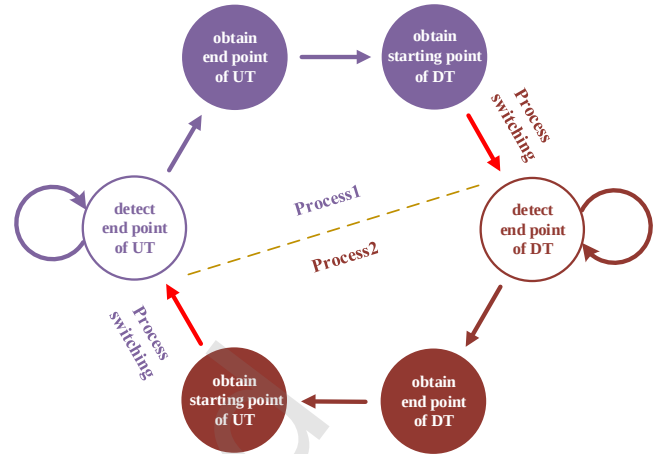


Fig. 3 The detection flow of the EMET.

exhalation, referred to as "down-trend" (DT). The starting point (the peak of the signal) and the end point (the trough of the signal) of DT correspond to the beginning and end of exhalation, respectively. Combined with the information representation method shown in Fig.1 and the above analysis, it is easy to know that the prerequisite of decoding is to detect and identify the endpoint information of UT and DT.

The traditional endpoint detection techniques process the signal by windowing method which requires careful setting of the sliding window size. When breathing frequency changes, missed detection is likely to occur. Moreover, windowing method is not conducive to the lightweight of the algorithm. To solve the above problems, we propose an extraction method for endpoints of trend (EMET) based on stream processing. Since the exhalation and inhalation actions are sequential, we can come to the following conclusion.

Conclusion 1: The end point of UT (or DT) is the starting point of the next DT (or UT), and the starting point of UT (or DT) is the end point of the previous DT (or UT). Once the end point detection of the current trend is completed, it is equivalent to the starting point detection of the next trend being completed.

According to Conclusion 1, EMET is mainly divided into two processes as shown in Fig.3. Process1 is used to extract the end point of UT and the starting point of DT. Process2 is used to extract the end point of DT and the starting point of UT. These two processes are executed sequentially and alternate in a loop. Once Process1 has completed, Process 2 begins. Once Process2 has completed, Process1 begins.

Let R_r and R_l record the end point and starting point of UT, respectively. Let F_r , and F_l record the end point and starting point of DT, respectively. T_R is used to record the dwell time of the current information in R_r . T_F is used to

record the dwell time of the current information in F_r . Let $\square^t$ and $\square^y$ represent time and amplitude of $\square$, respectively. For example, R_r^t and R_r^y represent the time and magnitude of R_r , respectively.

During system initialization, R_r , R_l , F_r and F_l are initialized using the first data P_1 received. Because of the similarity between the end point detection processes of UT and DT, we will take the detection of the end point of UT (Process1) as an example to introduce EMET.

Assuming that EMET is currently in Process1, the information stored in R_l is the starting point information of UT which output from the last Process2. The information stored in R_l remains unchanged until the end of Process1. The information currently stored in R_r , F_l and F_r are ‘suspected’ endpoint information. In Process1, F_l always satisfies $F_l = R_r$. Let P_i represent the currently received data, where $i \in \mathbb{N}^+$ is the data index. The subsequent operation is determined by comparing with P_i^y and R_r^y .

$$(1) P_i^y \geq R_r^y$$

The amplitude of received data P_i is not less than that of the ‘suspected’ end point of UT stored in R_r . Since the end point of UT is local maximum, P_i is a more eligible ‘suspected’ end point of UT. Therefore, update R_r with P_i and reset T_R .

$$\begin{cases} R_r = (P_i^t, P_i^y) \\ T_R = 0 \end{cases} \quad (1)$$

It is easy to conclude from Conclusion 1 that when R_r is updated, R_r should be used to update F_l and F_r , and reset T_F as follows:

$$\begin{cases} F_l = (R_r^t, R_r^y) \\ F_r = (R_r^t, R_r^y) \\ T_F = 0 \end{cases} \quad (2)$$

Remark: Due to the way of stream processing, EMET cannot immediately determine whether the information in R_r is the real end point of UT after updating R_r . With the continuous influx of subsequent data, when the dwell time T_R of the current information in R_r is greater than the preset threshold T_δ , the ‘suspected’ information in R_r can be determined to be the end point of UT. This operation has a certain degree of anti-noise. As shown in Fig.4, the amplitude of the preprocessed signal shows an increasing trend in the future. The random jitter caused by noise masks the local increasing trend of UT. Through the time threshold T_δ , EMET can overcome the local jitter caused by noise.

$$(2) P_i^y < R_r^y$$

At this point, EMET enters the stage of ruling on the

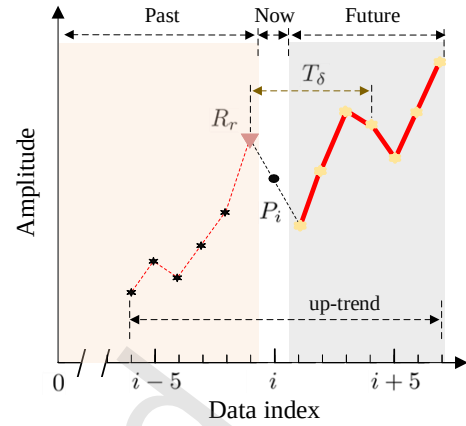


Fig. 4 Possible trend of future data.

‘suspected’ end point of UT. It takes time of T_δ from data being collected to it being confirmed as the end point of UT. At the same time, the system does not save historical data. If start searching for the end point of DT after the information in R_r being identified as the end point of UT, the data in time period T_δ will be missed. Therefore, when R_r is updated, F_r is updated as well as shown in Eq.(2). When the information in R_r is not updated and waiting to be adjudicated, it can be judged whether F_r needs to be updated by P_i based on the feature that the end point of DT is the local minimum.

If $P_i^y \leq F_r^y$, update F_r with P_i and reset T_F .

$$\begin{cases} F_r = (P_i^t, P_i^y) \\ T_F = 0 \end{cases} \quad (3)$$

If $P_i^y > F_r^y$, update T_F as follow

$$T_F = T_F + (P_i^t - P_{i-1}^t) \quad (4)$$

Since the information in R_r is not updated, update T_R as follow

$$T_R = T_R + (P_i^t - P_{i-1}^t) \quad (5)$$

When $T_R > T_\delta$, the end point detection of UT is complete. And then, the amplitude change A_j caused by UT can be calculated by Eq.(6)

$$A_j = |R_r^y - R_l^y| \quad (6)$$

where j denotes to the action sequence number. During the waiting period for determination about the information in R_r , F_r is updated. Therefore, when the result of A_j is obtained, R_l and R_r should be initialized with F_r and P_i respectively, and reset T_R immediately. When the next data sample enters, EMET goes directly to Process2.

Remark: There is no need to compare T_F and T_δ in Process1. Since $F_r^t \geq R_r^t$ in Process1, $T_F \leq T_R$ is easy to get. Therefore, T_R will exceed T_δ before T_F . The pseudo-code

of EMET is shown in Algorithm 1. Because the execution logic of Process1 and Process2 is symmetric, the pseudo-code of Process2 is omitted. According to Algorithm 1, we can easy to obtain that EMET only needs a small amount of logical comparison, assignment and addition operation to achieve the feature detection of respiration signal without storing historical data. So, EMET has the characteristics of low complexity and lightweight.

Algorithm 1 EMET

Input: P_i , currently received data after preprocessing.

Output: A_j , signal amplitude change of UT or DT.

% $flag = 0$ enters Process1

% $flag = 1$ enters Process2

```

1 if  $flag = 0$  then
2   if  $P_i^y \geq R_r^y$  then
3     Reset  $T_R$ ; Update  $R_r$  with  $P_i$ 
4     Reset  $T_F$ ; Reset  $F_r$  and  $F_l$  with  $R_r$ 
5   else
6     if  $P_i^y \leq F_r^y$  then
7       Reset  $T_F$ ; Update  $F_r$  with  $P_i$ 
8     else
9        $T_F = T_F + (P_i^t - P_{i-1}^t)$ 
10    end if
11     $T_R = T_R + (P_i^t - P_{i-1}^t)$ 
12    if  $T_R > T_\delta$  then
13       $j = j + 1$ 
14       $flag = 1$ 
15       $A_j = |R_r^y - R_l^y|$ 
16      Reset  $R_l$  with  $F_r$ 
17      Reset  $R_r$  with  $P_i$ ; Reset  $T_R$ 
18    end if
19  end if
20 else
21    % Process2 (omitted)
22 end if

```

2.3 Decoding

We use one “full beat” action to represent ‘0’ and two “half beat” actions to represent ‘1’. Therefore, the key to decoding is to identify the type of action. When users convey information through breathing, the process of controlling the breathing amplitude can be regarded as a “comparison” process^[28]. If the type of the current action is the same as that of the previous action (i.e., both are “full beat” actions or “half beat” actions), the user will use the same force to control the current action. Otherwise, the force used to control the current action will be determined based on the type of the previous action. We

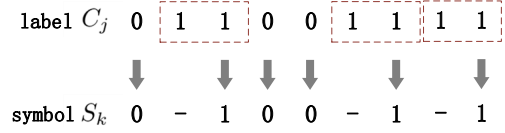


Fig. 5 Relationship between action label and symbol.

describe the above process using the breath control model^[28] as shown in Eq.(7).

$$\begin{cases} F_j = F_{j-1} + (C_{j-1} - C_j) \times \Delta F_j + \epsilon_j \\ \frac{A_j}{A_{j-1}} = \frac{F_j}{F_{j-1}} \end{cases} \quad (7)$$

where F_j is the strength of the control action, ΔF_j is the strength difference, $C_j \in \{0, 1\}$ is action label, $C_j = 1$ means the “half beat” action, $C_j = 0$ means the “full beat” action, and ϵ_j is the control error, $j \in \mathbb{N}^+$ is data index, A_j is the output of Algorithm 1. According to Eq.(7), we can obtain

$$\frac{A_j}{A_{j-1}} = 1 + \frac{\epsilon_j}{F_{j-1}} + (C_{j-1} - C_j) \times \frac{\Delta F_j}{F_{j-1}} \quad (8)$$

Obviously,

$$\frac{A_j}{A_{j-1}} = \begin{cases} 1 + \frac{\epsilon_j}{F_{j-1}}, & \text{when } C_j = C_{j-1} \\ 1 + \frac{\epsilon_j}{F_{j-1}} \pm \frac{\Delta F_j}{F_{j-1}}, & \text{when } C_j \neq C_{j-1} \end{cases} \quad (9)$$

Eq.(10) can be used to distinguish between the two cases in Eq.(9).

$$\frac{\max\{A_j, A_{j-1}\}}{\min\{A_j, A_{j-1}\}} > \tau \quad (10)$$

where τ is the threshold and $\tau = 1.4$. When the logic of Eq.(10) is true, it means that the adjacent action labels are different, that is, $C_j \neq C_{j-1}$; otherwise, $C_j = C_{j-1}$. We can use Eq.(11) to identify the action label.

$$C_j = \{C_{j-1} + |C_{j-1} - (A_j < A_{j-1})| \times (\frac{\max\{A_j, A_{j-1}\}}{\min\{A_j, A_{j-1}\}} > \tau)\} \bmod 2 \quad (11)$$

where mod is the modular operation. Based on Eq.(11), we can obtain action label in a recursive way, and can't get symbol information directly. Because the number of actions corresponding to ‘0’ and ‘1’ are different. As shown in Fig.5, when the action label is 0, the symbol 0 can be output directly. When the action label is 1, it needs to be judged and then output.

To achieve decoding, we propose a decoding method based on recursive processing. First we introduce a variable x_j with an initial value $x_1 = 0$. Then according to Eq.(12), its

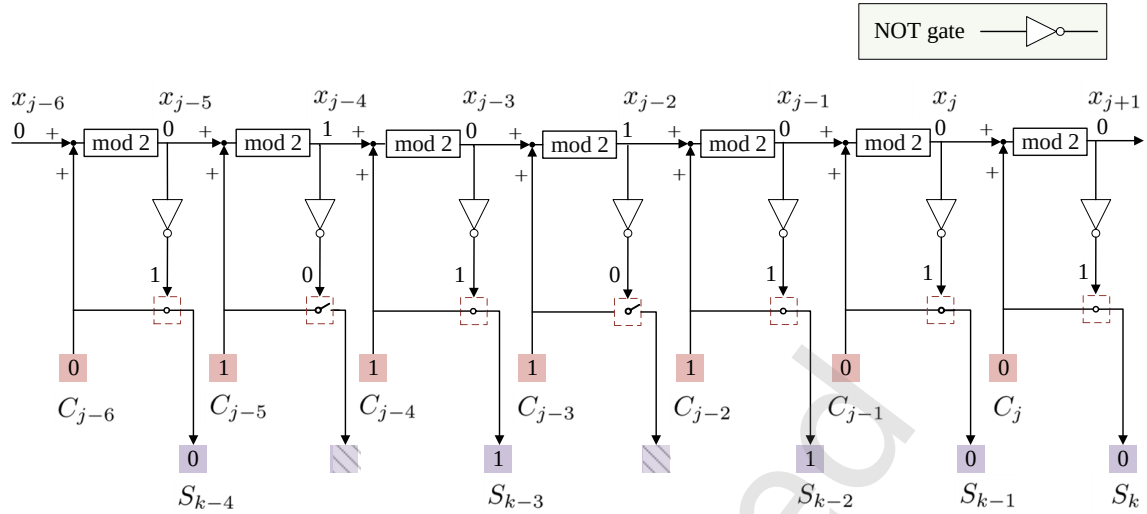
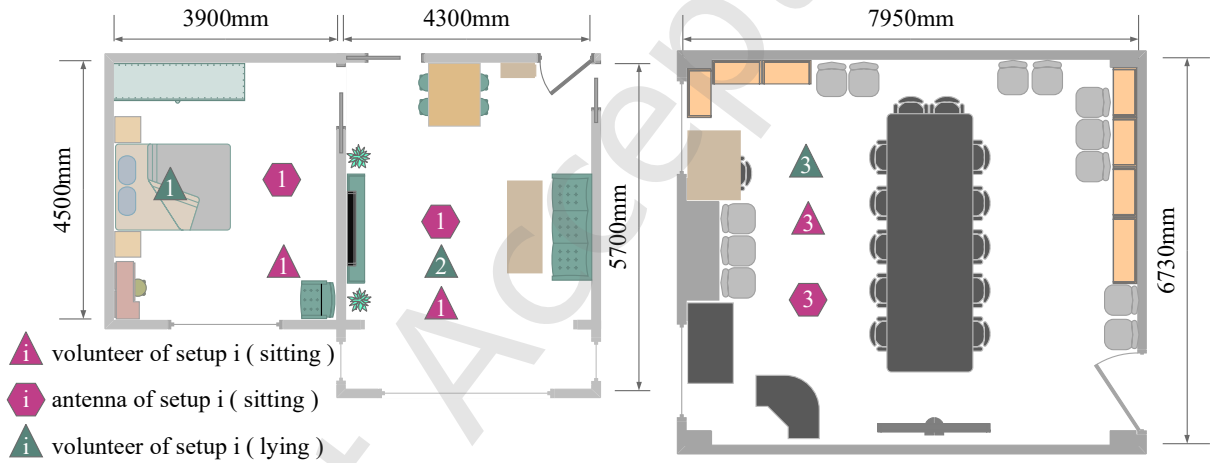


Fig. 6 An example of decoding.

Fig. 7 Experimental environments^[29].

subsequent value x_j can be obtained.

$$\begin{cases} x_1 = 0 \\ x_{j+1} = (x_j + C_j) \bmod 2 \end{cases} \quad (12)$$

Finally, we can use Eq.(13) to obtain the decoded output.

$$\begin{cases} S_k = C_j, k = k + 1 & \text{when } x_{j+1} = 0 \\ \text{no output} & \text{when } x_{j+1} = 1 \end{cases} \quad (13)$$

where S_k is the final output symbol, and $k \in \mathbb{N}^+$. To visually demonstrate the decoding process, we have created an example, as shown in Fig.6.

3 Experiments and Analysis

We implement our method by Matlab software and use commercial RFID devices to collect data for experiments. The device models are the same as ExHIBit^[29], and so is the experimental environment as shown in Fig.7. During the ex-

periment, we kept the values of thresholds T_δ and τ constant, with $T_\delta = 0.4$ and $\tau = 1.4$. We recruit 10 volunteers to participate in our experiments. The male to female ratio is 5:5 and aged between 25 and 52. Unless otherwise mentioned, the default setting will be adopted, that is, the volunteer is located at the position 3 shown in Fig.7 with the RFID reader antenna facing the RFID tag stuck to chest area of the volunteer's clothing, 1.5m apart. The information transmitted by volunteer is a binary random sequence. By default, experiment last 10 minutes for each set of parameters and each experiment is repeated 3 times. The evaluation metrics are detection rate (DR) and false positive rate (FPR)^[29].

3.1 Effect of Device Deployment

Based on the default settings, we evaluate the effect of distance and relative orientation between the RFID reader antenna

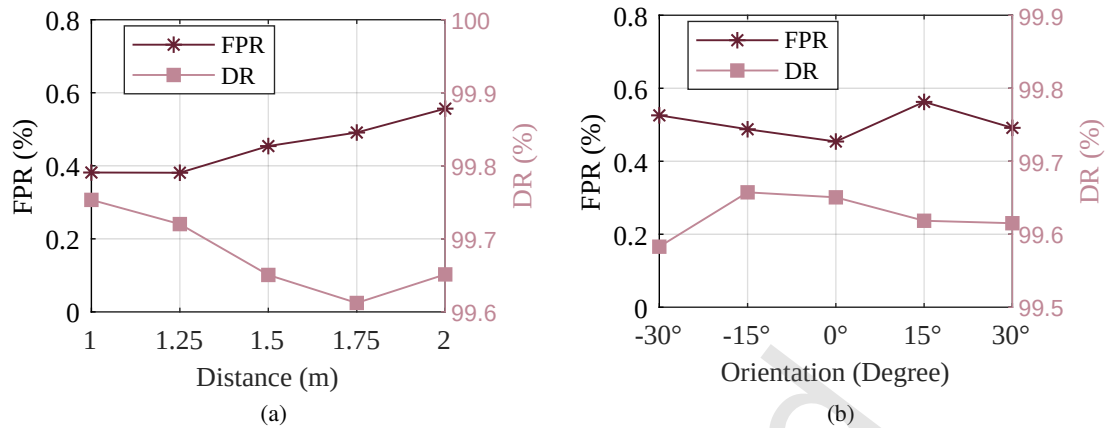


Fig. 8 (a) Effect of distance on performance. (b) Effect of orientation on performance.

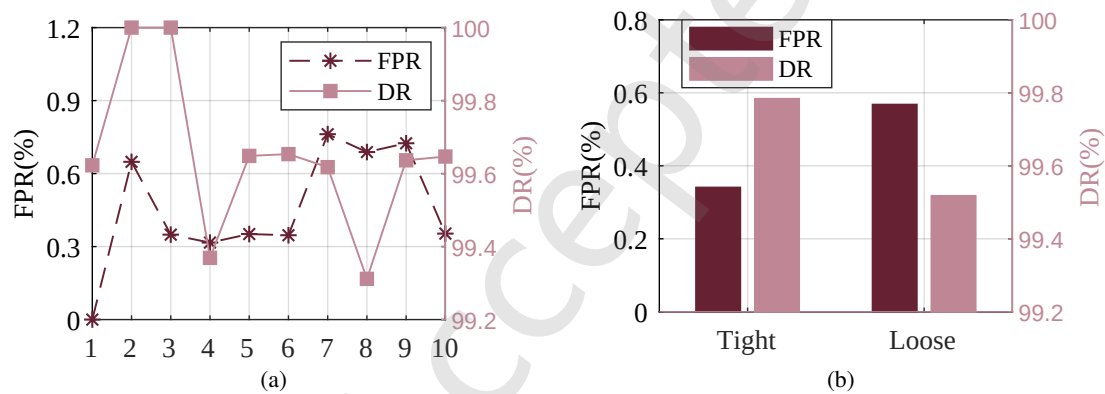


Fig. 9 (a) Effect of users on performance. (b) Effect of clothing on performance.

and the RFID tag on the system. We choose five different distances and five different orientations. As shown in Fig. 8, the performance of the system remains basically stable with the change of distance or orientation.

3.2 Effect of Different Users and Clothes

We number 10 volunteers as 1 to 10, of which No. 1 to No. 5 are female. Fig. 9(a) shows the test results of each volunteer under the default settings. We can conclude that there is little variation in the performance of BeaType between different volunteers, indicating that BeaType demonstrates good consistency between different users. In the experiment, five volunteers (numbers 4, 6, 7, 8 and 9) wear loose clothing (e.g., knitted woolen garments, warm pajamas, and loose clothing), while the others wear tight clothing (e.g., T-shirts and jackets). The data of these two groups of volunteers are counted and the results are plotted in Fig. 9(b). From the results on the graph, it is easy to see that the fit of the clothes has an effect on the performance of the system. This is because we attach the RFID tag to the chest area of the clothing.

During breathing, the chest undergoes rhythmic expansion and contraction. Tight-fitting clothing allows the tag to fit closer to the chest, forcing the tag to move synchronously with the chest, thereby obtaining more obvious signal characteristics. When clothing is loose, the fit between the RFID tag and the chest is reduced, and sometimes it is impossible to fully follow the movement of the chest. Nevertheless, chest motion still induces multipath effects, so the phase signals of the RFID tag can still effectively reflect breathing characteristics.

We recommend that users wear close-fitting clothing as much as possible, and that RFID tags be attached to their underwear. Try to face the RFID antenna to ensure that the longitudinal undulations of the chest can be modulated to the phase signal of the RFID tag to the greatest extent. When attaching the RFID tag, try to stick the tag to the largest area where the chest rises and falls. If abdominal breathing is used, stick the RFID tag to the stomach. The redundant deployment of multiple RFID tags can improve the signal-to-noise ratio of respiratory signals by designing signal fusion algorithms for multiple RFID tags.

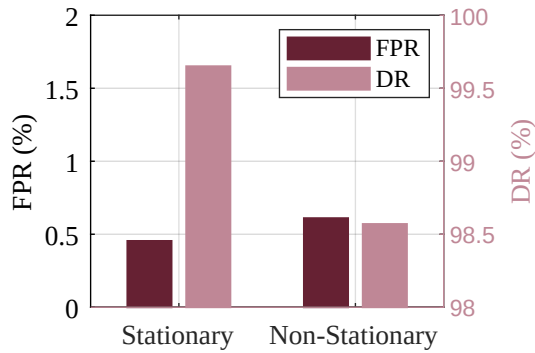


Fig. 10 Effect of non-stationary breathing on performance.

3.3 Effect of Non-stationary Breath

Two volunteers are randomly selected to carry out the experiment of non-stationary breath. Based on the default setting, the volunteers randomly increased or decreased the breathing rate. The maximum breathing rate is about twice the normal breathing rate. As shown in Fig. 10, DR of the system under non-smooth breathing is 98.57%, and FPR is 0.61%, which is somewhat different from that under smooth breathing, but the performance can still meet the needs of practical applications.

3.4 Effect of Posture and Environment

Based on the default settings, the performance of the system is evaluated at the three different locations shown in Fig. 7 with sitting posture and lying posture, respectively. As shown in Table 2, the system achieves comparable performance in both postures, with no significant performance differences in the three locations.

Table 2 Effect of posture and environment.

Environment	Sitting		Lying	
	DR	FPR	DR	FPR
1	99.57%	0.55%	99.67%	0.46%
2	99.66%	0.48%	99.65%	0.51%
3	99.65%	0.45%	99.69%	0.47%

3.5 Text Input Speed

We adopt words per minute (WPM) defined in WiMorse^[5] as a measure of text input speed. Thirty different sentences are randomly generated, and each volunteer randomly selects three from them. For common phrases, volunteers can use abbreviations to improve the input speed. Under three coding rules of Bcode^[28], GBcode^[28] and Huffman encoding, the average text input speed of our method is 1.58WPM, 1.71WPM and 1.9WPM respectively. In the case of using

Huffman coding and allowing the use of abbreviations, the input speed can reach up to 2.13WPM.

The input speed of BeaType is higher than that of ReType^[28] and ExHBit^[29] due to the improved information representation, but lower than that of methods that require interaction with screen^[26, 27]. For example, the input speed of VIWA^[26] is close to 8WPM. However, our method is still advanced. Methods that interact with the screen cannot provide services for patients with visual impairment. Our method does not require interaction with the screen and is suitable for all users who can breathe on their own. In addition, our method allows users to freely express their intentions, while traditional non-interactive methods^[23–25] do not.

4 Effect of Key Parameters

4.1 Impact on Detection Capabilities

We use simulation methods to explain the impact of T_δ and τ . Since T_δ affects the detection performance of signal feature points, we adopt DR and FPR to evaluate the impact of T_δ . DR refers to the percentage of true beats that are successfully detected, and FPR refers to the proportion of beats output by the system that are not true beats. Since τ affects the recognition accuracy of beat label, we leverage the recognition error rate (ER) of beat label to evaluate the impact of τ . ER refers to the ratio of incorrectly judged beat labels to the total number of beat labels output by the algorithm. Misjudged beat labels include two situations: one is that the true beat is detected, but its label is misjudged; the other is that the system detects a false beat and gives a false beat label.

During simulation, we use line segment to simulate the beat. The amplitude of “full beat” is 1, and the amplitude of “half beat” is 0.5. Assuming a breathing rate of 40 breaths per minute, so the duration of “full beat” is 0.75s and the duration of “half beat” is 0.37s. The sampling rate of the data is set to 120. We randomly generate 10,000 binary codes and then convert them into noise-free simulated signals according to the mapping relationship. During simulation, T_δ is increased from 0.1 to 1.2 with a step size of 0.05; τ is increased from 1.2 to 1.8 with a step size of 0.1. When adding noise to the signal, the signal-to-noise ratio (SNR) is increased from 10dB to 30dB with a step size of 2dB. During the simulation, we do not filter the noisy signal to retain all of its noise.

Due to the large amount of simulation signal data, we have wrote a special program to automatically determine whether real feature points are detected in our previous work^[28, 29]. And the method is as follows. We extract the timestamp information of adjacent target feature points in the noiseless simulation signal in advance. If at least one feature point is

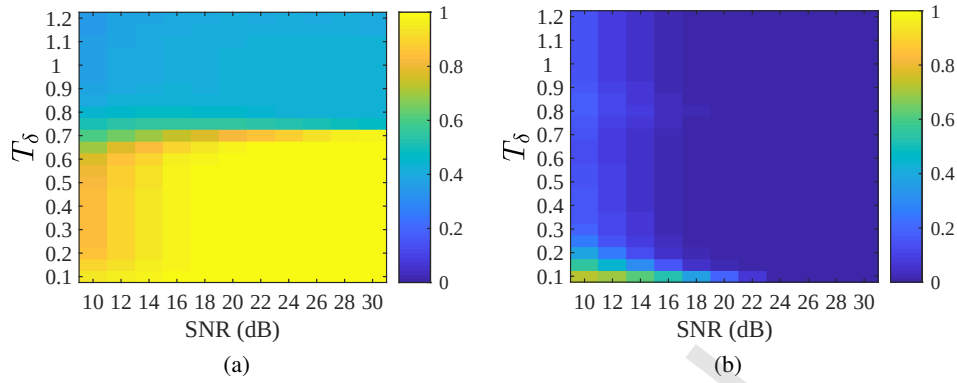


Fig. 11 (a) DR at different T_δ and SNR. (b) FPR at different T_δ and SNR.

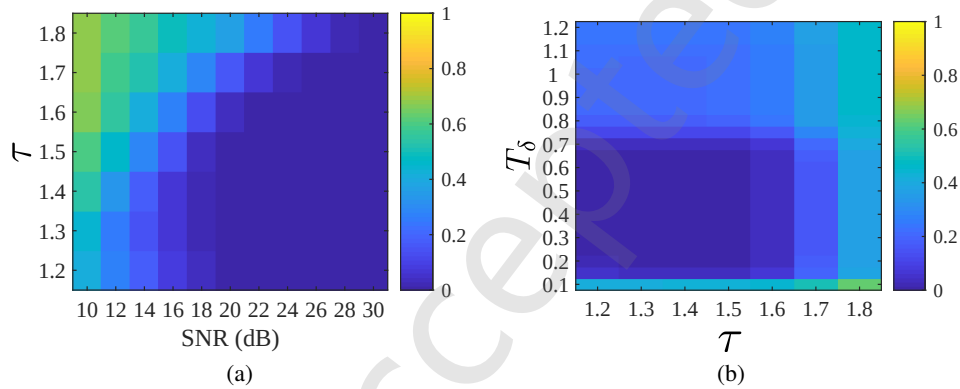


Fig. 12 (a) ER at different τ and SNR when $T_\delta=0.3$. (b) ER at different T_δ and τ when SNR=20dB.

detected in the noisy simulated signal within the range of these two timestamps, it is considered that the true feature point within this time range has been successfully detected. But we have found in subsequent experiments that the calculation results of this judgment method have deviations in the case of low SNR and can only be used for qualitative analysis. Therefore, we have improved the judgment rule in this paper. If the deviation between the timestamp of the endpoints of the beat detected from the noisy simulated signal and the timestamp of the corresponding beat endpoints in the noise-free simulated signal is within 0.1, the detection is considered successful. Otherwise, it is judged as a false positive point.

In addition, we need to explain a situation that may be encountered when calculating the recognition ER of beat labels. Since we use a recursive beat label recognition method, the order of the true labels will be misaligned when a false positive beat occurs. In this case, we first use Eq.(11) recognize all beat labels, including those of false positive beat labels. When counting ER, false positive beat labels are directly counted into the number of error labels. The label of the misaligned true beat should be compared with the ground truth

beat label at its intended position. If the label identification types are inconsistent, they will be counted into the number of erroneous labels. Finally, ER is calculated based on the counting results.

Fig.11 shows the detection performance under different combinations of T_δ and SNR. From Fig.11(a), we can see that DR drops sharply once T_δ increases to 0.75 when SNR is kept unchanged (assuming it is 10dB). This is because when T_δ exceeds 0.75, its value surpasses twice the duration of “half beat”, which triggers a significant number of missed detections. As shown in Fig.11(b), FPR gradually decreases as T_δ increases. Therefore, T_δ cannot be too large or too small. Obviously it is appropriate for us to set T_δ to 0.3 in practice.

Fig.12 illustrates the impact of τ on algorithm performance. Fig.12(a) shows the beat label recognition error rate under different combinations of τ and SNR when $T_\delta=0.3$. It is evident that ER increases as τ increases when SNR remains constant. This is because the amplitude ratio of a full beat to a half beat is set to 2 in the simulation. The closer τ is to this ratio, the more sensitive the algorithm is to uncertain

fluctuations caused by noise. Fig. 12(b) shows ER under different combinations of τ and T_δ values when SNR is 20dB. There is a high-performance area near the lower left corner ($T_\delta \in [0.2, 0.6]$). The two threshold values we selected ($T_\delta = 0.3$, $\tau = 1.4$) fall precisely within this region.

4.2 Impact on Real-time Performance

Parameter τ appears in Eq. (11) and plays a role in recognizing beat labels. Since it is involved in only a single logical comparison, the resulting computational delay is negligible.

Some noise still remains in the preprocessed signal, so when the system receives a suspected feature point (i.e., the endpoint of the beat action), it cannot be immediately confirmed as a valid endpoint. Because this point may just be a false feature point caused by noise. To this end, the system adopts a “continuous observation” mechanism: from the appearance of the candidate point, it continues to observe for a fixed period of time T_δ . If a better candidate point appears during this period, the original candidate point is replaced, and the observation timer is cleared and restarted; only when it is not replaced by a better candidate point within the entire observation time period T_δ is the candidate point finally confirmed as the real endpoint. Obviously, this mechanism introduces a fixed delay, that is, after the real signal feature point arrives, the system needs to wait T_δ seconds before outputting the confirmation result. We have pointed out in previous analysis that T_δ is not as small as the better. Too small T_δ will make the system susceptible to residual noise interference and cause false detections. In order to ensure the robustness and stability of system detection, $T_\delta = 0.3s$ is taken after trade-offs. This value is within the acceptable range of delay and effectively suppresses the impact of noise.

5 Conclusion

With the help of RFID devices, we design BeaType to help severely paralyzed patients communicate with others. We propose a method to transmit information using the beat feature of breathing. We design a feature extraction method to extract the amplitude features of breathing actions. In addition, we give a decoding method based on recursive processing. The algorithms of the whole scheme are designed by the way of stream processing, which makes our method lightweight. Comprehensive experiments show that our method can work effectively in different scenarios and for different users.

The pursuit of faster input speed is an important goal in the research of alternative communication techniques. However, the universality of the solution is equally important. This study is based on the universality of the solution and proposes

BeaType which does not require users to have normal vision and does not require interaction with the screen. Therefore, in terms of efficiency, there is a certain gap compared to existing interactive methods.

From the perspective of healthy individuals, the efficiency of our proposed solution might be so low as to be unbearable. However, it can win the favor of patients. The reason why our method is precious lies in the fact that it allows patients to freely express their wishes, rather than merely being able to answer “yes” or “no”. Just as Mr. Plotkin said, “The speed of this self-expression is less important to individuals who, put bluntly, have no other options.”^[32]

Although context-aware word prediction is beyond the scope of this paper, we want to briefly explore the potential feasibility of integrating a standard language model into the BeaType framework. As the user enters characters one by one, the standard language model assigns a prior probability distribution to the next character based on the decoded prefix. Based on this prior information, the system can realize automatic word completion, thereby reducing the number of breathing coding bits required per word. Furthermore, when the decoded character sequence conflicts with linguistic rules, the model can assist in recommending more reasonable word candidates, thereby improving input accuracy. It should be noted that the implementation details and performance evaluation of the above integration scheme still require further research. We believe this direction has significant practical value, and future work is expected to greatly improve actual input efficiency based on this.

Acknowledgment

This work was supported in part by Fundamental Research Program of Shanxi Province (No. 202403021221180), the Scientific and Technological Innovation Programs of Higher Education Institutions in Shanxi (No. 2023L288), National Natural Science Foundation of China (No. 61972273), National Key Scientific Instrument Projects (No. 62027819).

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

Reference

- [1] G. Logroscino, M. Piccininni, and B. Marin, et al., Global, regional, and national burden of motor neuron diseases 1990–2016: a systematic analysis for the global burden of disease

- study 2016, *The Lancet Neurology.*, vol. 17, no. 12, pp. 1083-1097, 2018.
- [2] V. Feigin, B. Stark, and C. Johnson, et al., Global, regional, and national burden of stroke and its risk factors, 1990-2019: a systematic analysis for the global burden of disease study 2019, *The Lancet Neurology.*, vol. 20, no. 10, pp. 795-820, 2021.
 - [3] S. James, A. Theadom, and R. Ellenbogen, et al., Global, regional, and national burden of traumatic brain injury and spinal cord injury, 1990-2016: a systematic analysis for the global burden of disease study 2016, *The Lancet Neurology.*, vol. 18, no. 1, pp. 56-87, 2019.
 - [4] M. Wallin, W. Culpepper, and E. Nichols, et al., Global, regional, and national burden of multiple sclerosis 1990-2016: a systematic analysis for the global burden of disease study 2016, *The Lancet Neurology.*, vol. 18, no. 3, pp. 269-285, 2019.
 - [5] K. Niu, F. Zhang, and Y. Jiang, et al., WiMorse: a contactless morse code text input system using ambient WiFi signals, *IEEE Internet of Things Journal.*, vol. 6, no. 6, pp. 9993-10008, 2019.
 - [6] A. Marathe, S. Bawanthade, and R. Bele, et al., Morse code based two-Way communication device for visually impaired and mute, in *2025 3rd International Conference on Device Intelligence, Computing and Communication Technologies.*, Dehradun, India, 2025, pp. 170-175.
 - [7] X. Wang, X. Zhao, and C. Feng, et al., mmFinger: Talk to smart devices with finger tapping gesture, *IEEE Transactions on Mobile Computing.*, vol. 24, no. 5, pp. 3537-3551, 2025.
 - [8] R. Gao, W. Li, and J. Liu, et al., WiCGesture: Meta-motion-based continuous gesture recognition with Wi-Fi, *IEEE Internet of Things Journal.*, vol. 11, no. 9, pp. 15087-15099, 2024.
 - [9] Y. Zhang, W. Sun and M. Li, WiRITE: General and practical Wi-Fi based hand-writing recognition, *IEEE Transactions on Mobile Computing.*, vol. 23, no. 4, pp. 2943-2957, 2024.
 - [10] P. Seshadri, S. Dananjayan and H. F. T. Ahmed, Hand detection and Morse Code translation for alternative communication, in *2023 International Conference on System, Computation, Automation and Networking (ICSCAN).*, PUDUCHERRY, India, 2023, pp. 1-6.
 - [11] C. Zhang, Y. Hou, and J. He, et al., Gesture Recognition with Focuses Using Hierarchical Body Part Combination, *Tsinghua Science and Technology.*, vol. 30, pp. 1583-1599, 2025.
 - [12] M. R. M. Bastwesly, K. Kai, and H. Choi, et al., Wi-Nod: Head nodding recognition by Wi-Fi CSI toward communicative support for quadriplegics, in *2023 IEEE Wireless Communications and Networking Conference (WCNC).*, Glasgow, United Kingdom, 2023, pp. 1-6.
 - [13] J. Lee, J. Kim, and G. Kim, et al., A simplified morse-coded eyewear-type transducer for touchless communication via complex head gestures, *Sensors and Actuators A: Physical.*, Volume 396, pp. 1-10, 2025.
 - [14] X. Wang, L. Xiong, and W. Dong, et al., Flexible strain sensor based on conductive Hydrogel/KC@PDMS for neck motion control wheelchair using EMD-LSTM algorithm, *IEEE Sensors Journal.*, vol. 24, no. 3, pp. 4079-4090, 2024.
 - [15] N. Zendehelel, K. G. Zadeh, and H. Chen, et al., Hands-Free UAV Control: Real-time eye movement detection using EOG and LSTM networks, *IEEE Access.*, vol. 13, pp. 101852-101868, 2025.
 - [16] K. Li, D. Chen, and Z. Rao, et al., A multimodal asynchronous human-machine interaction method based on electrooculography and speech recognition for wheelchair control, *IEEE Sensors Journal.*, vol. 24, no. 23, pp. 39195-39205, 2024.
 - [17] A. Anand, D. P. Jagannath, and V. P. Menon, et al., An eye gesture-controlled wheelchair base, in *2025 1st International Conference on Smart and Intelligent Systems (SISCON).*, Thiruvananthapuram, India, 2025, pp. 1-6.
 - [18] C. Chang, Y. Hsu, and K. Pai, et al., A myoelectric signal-driven intelligent wheelchair system incorporating occlusal control for assistive mobility, *Electronics.*, vol. 14, no. 19, pp. 1-19, 2025.
 - [19] S. Li, P. Wang, and X. Yu, et al., GANet: A convolution neural network with parallel convolutions and graph-based attention mechanism for event-related potential classification in brain-computer interface task, *Tsinghua Science and Technology.*, vol. 31, pp. 920-931, 2026.
 - [20] C. Tang, D. Jiang, and Y. Guo, et al., Copula transfer entropy-based channel selection for MEG motor imagery brain computer interfaces, *Tsinghua Science and Technology.*, vol. 31, pp. 1474-1486, 2026.
 - [21] J. Zhu, K. Li, and S. Chen, et al., Smart ward control based on a wearable multimodal brain-computer interface mouse, *IEEE Transactions on Neural Systems and Rehabilitation Engineering.*, vol. 34, pp. 638-649, 2026.
 - [22] Y. Jiang, K. Li, and Y. Liang, et al., Daily assistance for amyotrophic lateral sclerosis patients based on a wearable multimodal brain-computer interface Mouse, *IEEE Transactions on Neural Systems and Rehabilitation Engineering.*, vol. 33, pp. 150-161, 2025.
 - [23] Y. Elsahar, K. Bouazza-Marouf, and D. Kerr, et al., Breathing pattern interpretation as an alternative and effective voice communication solution, *Biosensors.*, vol. 8, no. 2, pp. 48, 2018.
 - [24] Y. Elsahar, S. Hu, and K. Bouazza-Marouf, et al., A study of decodable breathing patterns for augmentative and alternative communication, *Biomedical Signal Processing and Control.*, vol. 65, pp. 102303, 2021.
 - [25] S. Zou, L. Tao, and G. Wang, et al., Humidity-based human-machine interaction system for healthcare applications, *ACS Applied Materials & Interfaces.*, vol. 14, no. 10, pp. 12606-12616, 2022.
 - [26] T. Bodaghi, M. Karami, and H. Jazayeriy, VIWA: computer interface device for paralyzed people using breath pressure, *Biomedical Engineering Applications Basis and Communications.*, vol. 28, no. 1, pp. 1650004, 2016.



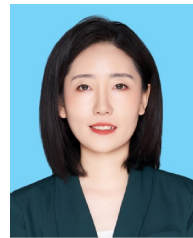
- [27] N. Sayama, N. Komatsu, and K. Sawanobori, et al., A breath switch for secure password input, in *Intelligent Computing-Proceedings of the Computing Conference.*, Cham, Switzerland, 2019, pp. 1150-1154.
- [28] Q. Wang, J. Zhao, and S. Xu, et al., ReType: Your breath tells your mind! *IEEE Internet of Things Journal.*, vol. 8, no. 11, pp. 9436-9449, 2021.
- [29] Q. Wang, J. Zhao, and S. Xu, et al., ExHIBit: Breath-based augmentative and alternative communication solution using commercial RFID devices, *Information Sciences.*, vol. 608, pp. 28-46, 2022.
- [30] T. Liu, L. Yang, and X. Li, et al., TagBooth: Deep shopping data acquisition powered by RFID tags, in *2015 IEEE Conference on Computer Communications (INFOCOM).*, Hong Kong, China, 2015, pp. 1670-1678.
- [31] X. Wang, C. Yang, and S. Mao, ResBeat: Resilient breathing beats monitoring with realtime bimodal CSI data, in *2017 IEEE Global Communications Conference (GLOBECOM).*, Singapore, 2017, pp. 1-6.
- [32] A. Plotkin, L. Sela, and A. Weissbrod, et al., Sniffing enables communication and environmental control for the severely disabled, *Proceedings of the National Academy of Sciences.*, vol. 107, no. 32, pp. 14413-14418, 2010.



Qiang Wang received the M.S. degree in circuits and systems from North China University of Technology, China, in 2013, and the Ph.D. degree in electronic science and technology from the College of Information and Computer, Taiyuan University of Technology, China, in 2022. He is currently a lecturer at the College of Computer and Network Engineering, Shanxi Datong University, Datong, China. His research interests include signal processing, Internet of Things, mobile computing, and intelligent perception. He received the ACM China Council Taiyuan Chapter Honored Doctoral Dissertation Prize in 2023.



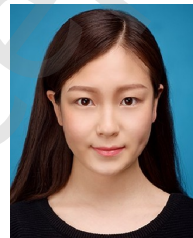
Dengao Li received the Ph.D. degree from Taiyuan University of Technology, China, in 2010. He is a professor at the College of Computer Science and Technology (College of Data Science), Taiyuan University of Technology. His main research interests include computer vision and pattern recognition.



Shuang Xu received the PhD degree in computer application technology from Northeastern University, China in 2019. She is currently an associate professor at the College of Artificial Intelligence, Taiyuan University of Technology, Shanxi, China. Her research interests include satellite Internet, mobile edge computing, and space edge intelligence. She received the IEEE MSN best paper and ACM China council rising star.



Xiaoxia Song received the M.S. degree in computer software and theory from Guangxi Normal University, China, in 2005, and the Ph.D. degree in intelligent information processing from Xidian University, China, in 2013. She is currently a professor at the College of Computer and Network Engineering, Shanxi Datong University, Datong, China. Her current research interests include data mining, compressed sensing theory, and optimization calculation. She is a Senior Member of the China Computer Federation (CCF).



Yajun Li received the M.S. degree in applied mathematics from Guangxi University, China, in 2020. She is currently pursuing a Ph.D. degree in electronic science and technology from the College of Electronic Information Engineering, Taiyuan University of Technology, Taiyuan, China. Her research interests include signal processing, intelligent sense, and the Internet of Things.



Huiting Zhang received the Ph.D. degree from Taiyuan University of Technology, Taiyuan, China, in 2025. She is currently a lecturer at the College of Artificial Intelligence, Taiyuan University of Technology, Shanxi, China. Her main research areas encompass artificial intelligence, data analytics, and data processing.



Jumin Zhao received the Ph.D. degree from Taiyuan University of Technology, Taiyuan, China, in 2008. She is a professor at the College of Electronic Information Engineering, Taiyuan University of Technology. Her main research interests include intelligent perception, signal processing, Internet of Things, and mobile computing.