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RESEARCH ARTICLE

A Personalized Contactless Emergency Aid System Designed for Individuals With Profound Physical Disabilities

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ABSTRACT This study proposes the development of a contactless emergency assistance system designed for individuals with severe physical disabilities (tetraplegia and no voice but normal mouth movements) to address the limitations of traditional emergency bells in sudden emergencies. The core technology of the system includes artificial intelligence facial recognition and fuzzy motion algorithms to identify facial movements. After the auxiliary signal is triggered, the system uses Message Queuing Telemetry Transport (MQTT) technology to activate warning lights and speakers. The signal is then transmitted to the LINE application on a computer or smartphone platform via Wi-Fi, notifying caregivers to provide timely assistance. Experimental results show that the system has a user-friendly interface and an accuracy rate of about 96.69%. This study is the successful development of an emergency assistance system controllable by quadriplegic patients. The one-to-many alarm device can establish a safe net, effectively help individuals with severe physical disabilities proactively seek help, reduce the risk of accidents, and alleviate caregiver shortages. For quadriplegics, this technology offers a unique alternative with significant advantages over commercially available manually operated or voice command call bells.

INDEX TERMS Quadriplegia, emergency, artificial intelligence, MQTT.

I. INTRODUCTION

Physical functional impairment refers to injuries affecting the arms, trunk, or legs that impact a patient's ability to perform activities. Severe physical disabilities can result in the loss of the patient's ability to independently carry out daily activities due to physical limitations, such as paralysis or difficulty in movement. This includes patients with conditions like cerebral palsy, spinal cord injuries, motor neuron diseases, and others. Patients with limb paralysis, while having normal brain function and clear consciousness, may be unable to engage in work and can only lie in bed. Patients with language communication abilities can express their needs through shouting, while those without language capabilities must rely entirely on the assistance of caregivers. If caregivers are not present, patients are unable to call for help independently, leading to a sense of helplessness and increasing the risk of accidents. Therefore, the call bell is an extremely important aid for these patients.

This study proposes the development of a contactless emergency assistance system designed for individuals with severe physical disabilities (tetraplegia and no voice but

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normal mouth movements) to address the limitations of traditional emergency bells in sudden emergencies. There are many types of call bells on the market, each with different features and functions. Here are some common types of call bells [1], [2], [3], [4]: Push-button call bells are the simplest form and typically require the push of a button to trigger an audible alarm and/or light. The wireless remote control call bell uses wireless technology to allow patients to trigger the call bell at any time by carrying a small remote control. Sound Sensor Call Bells use sound sensors to detect the patient's voice and trigger an alarm when a specific sound, such as shouting, is detected. Pressure-sensitive call bells mounted on the patient's mattress or chair sound an alarm when a change in pressure is detected, such as when the patient gets up or moves. Smart call bells are equipped with smart technology, such as connectivity with smartphone apps, allowing them to send notifications to caregivers or family members. Voice-activated call bells allow patients to use voice commands to trigger the call bell and are especially beneficial for patients who are unable to perform hand movements. Wearable call bells are designed in a wearable form so that patients can easily wear and activate the call bell. Traditional call bells are simple and easy to operate, triggering audible and visual alarms with the push of a button to notify caregivers to come and assist. But for patients with quadriplegia, normal brain function, and no voice, this surgical method is simply unusable. They are unable to perform simple pressing movements, so it is necessary to develop a call bell system suitable for their use, aiming to improve their life safety.

Research in the academic community regarding call bells is still relatively limited, and current studies can be broadly categorized into two types [5], [6], [7]. Firstly, there is the commonly used emergency call bell system in hospitals integrated with the Android system for message notifications. Pressing the call button [7] alerts healthcare personnel to provide assistance. The second type involves wearable devices [5], [6] that require prolonged wearing for measuring physiological signals for analysis [5]. Comfort becomes a crucial factor in the consideration of long-term wear. However, wristwatch-style emergency devices [6] still require manual operation to issue notifications in emergency situations. These supplementary devices, whether in commercial or academic settings, still require manual or voice control. However, they have not successfully addressed the calling challenges encountered by individuals with significant limb paralysis.

In recent years, artificial intelligence image processing technology has flourished [6], [7], [8], [9], [10], [11], [12], [13], [14]. Most artificial intelligence image processing technologies require the preparation of a large amount of graphics or image data for classification learning of new unknown objects. An active appearance model (AAM) is a computer vision algorithm for matching a statistical model of object shape and appearance to a new image. The AAM [9] is a generalization of the widely used Active Shape Model approach but uses all the information in the image region covered by the target object, rather than just that near modeled edges. Eye gaze tracking plays an important role in various fields, human-computer interaction, virtual and augmented reality, and in identifying effective marketing solutions in an effective manner. The eye gaze tracker does not always work accurately [13], even the best eye trackers are used to provide an accuracy of 0.58 of visual angle, but it cannot work in a dark environment. A low-cost camera-based framework for eye gaze estimation [14], the experiment so performed shows that the proposed method has shown considerable performance using CNN architecture and achieves an accuracy of 84.3% approx.

The transmission of emergency distress signals can be categorized into two types: wired and wireless. Wired signals offer higher reliability but have shorter transmission distances and require complex installation. Conversely, wireless signals are easier to install and have longer transmission distances. Wireless Emergency Alerts (WEAs) in the United States are brief emergency messages disseminated by authorized federal, state, local, tribal, and territorial public alerting agencies. Without the need to download an app or subscribe to a service, WEAs can be sent to mobile devices to alert individuals in danger. These messages are short and convey crucial, immediate information that could save lives. This technology [15] is well-suited for use in communication aids and can warn the public of an impending natural or human-made disaster.

In summary, currently utilized emergency auxiliary devices can be categorized into two main types: one is a push-button device that activates an alarm when triggered, while the other is an intercom device utilizing telephone communication to request assistance. Nevertheless, these conventional devices are unsuitable for individuals with severe physical disabilities (tetraplegia and no voice but normal mouth movements). In recent years, with the swift advancement of artificial intelligence technology [6], [10], [11], numerous breakthroughs have emerged. Consequently, the objective of this research is to develop an emergency support system powered by artificial intelligence (AI) that functions without physical contact. This pioneering system will leverage sophisticated AI facial recognition and fuzzy motion algorithms to identify specific mouth movements, emit a distress signal, and subsequently notify caregivers and distant family members of the situation. By adopting this innovative approach, the system can enable proactive, and immediate emergency calls, to effectively mitigate the risk of accidents.

II. METHOD

This study establishes the non-contact emergency assistance system (NCEA), which relies on artificial intelligence image recognition to trigger emergency events by recognizing specific facial movements. The system architecture of the NCEA is shown in Figure 1, and it consists of a webcam and an embedded system such as Raspberry Pi 4. The artificial

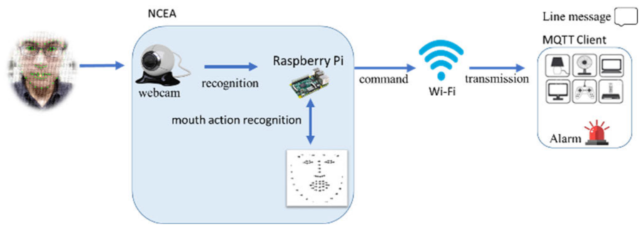


FIGURE 1. The architecture of the NCEA.

intelligence image recognition module, Dlib, is loaded into the embedded system to capture images at a rate of more than 12PF per minute. The Dlib module of AAM [9] is utilized for artificial intelligence image recognition, which is a C++ language library mainly applicable to machine learning, image processing, image recognition, etc. This open-source and free module is based on the Berkeley Software Distribution license terms. The module extracts 68 facial landmarks through Dlib. Autonomous movements of body parts (such as eyes and mouth) can trigger specific actions or expressions based on the fuzzy motion recognition algorithm to determine if a distress signal has been triggered.

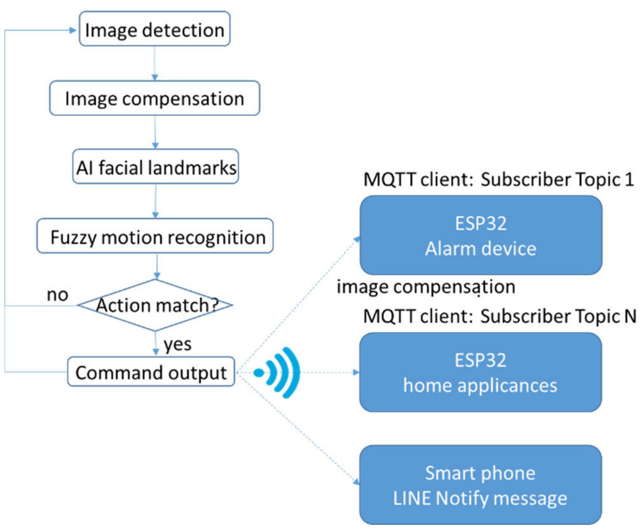


FIGURE 2. The operation flowchart of the NCEA system.

The operation flow of the NCEA system is depicted in Figure 2. When the action comparison is correct, corresponding commands can be sent via Wi-Fi to control alarm equipment, direction indication (for outdoor use), home appliance control, and to send information to caregivers or family members.

This research has the functions of auxiliary communication, smart home appliance control [16], [17], and danger warning. It can solve the problem of severe physical disability patients being unable to seek help proactively and in a timely manner, thus preventing accidents.

A. THE NCEA SYSTEM DESIGN

The NCEA system consists of two parts, including the NCEA software developed by Python programming and the alarm device developed by ESP32 microprocessor. The software interface design and alarm hardware circuit design of NCEA system as follows:

1) SOFTWARE INTERFACE DESIGN

The AI face feature extraction and fuzzy motion recognition algorithms of the NCEA system were created using Python 3.9 and integrated into a Raspberry Pi 4. The system communicates with smartphones via the LINE notification protocol and with the microcontroller ESP32 via the Message Queuing Telemetry Transport (MQTT) protocol [18] to send alert messages. By subscribing to MQTT messages, the system can activate or deactivate the alarm and even control household appliances. The MQTT broker server is built into the Raspberry Pi OS system. Users only need to apply for a fixed IP network line, and the alarm devices can be used without borders. When using it with multiple users, you only need to customize the name of the broker server and message topic.

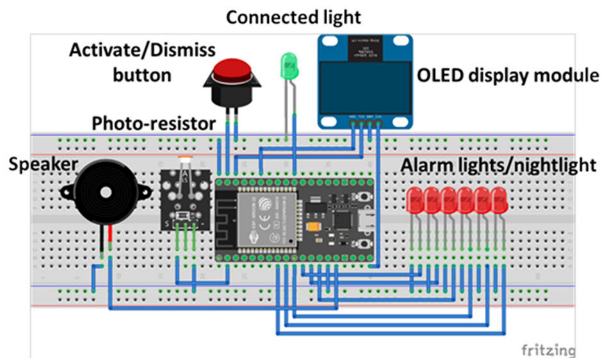


FIGURE 3. Alarm circuit design.

2) ALARM HARDWARE CIRCUIT DESIGN

The alarm device is built around the ESP32 microcontroller (depicted in Figure 3) which features an active/dismiss button, a Wi-Fi connection LED indicator, six LED warning lights, a speaker, a photoresistor, and an interactive OLED display module. The active/dismiss button enables caregivers to manually release the alarm or send an alert message to notify others. The OLED display module displays directional information to caregivers, enabling them to comprehend the patient's intentions. Additionally, a photo-resistor equips this device with a nightlight function.

The alarm hardware circuit can be incorporated into any preferred 3D models, such as those in the shape of pumpkins or Moai statues, etc. Additionally, the design of the night light can provide sufficient illumination for the camera and assist caregivers in attending to the subjects during nighttime hours.

B. IMAGE DETECTION AND COMPENSATION

In the image capture part of this research, only a webcam with 2 million pixels or more is required. The effectiveness of the NCEA system might be susceptible to factors like the surrounding lighting conditions. This variable could potentially have repercussions on the overall accuracy of the NCEA system's outcomes.

Regarding the impact of lighting, OPENCV offers pertinent compensation functions designed to mitigate the destabilizing effects of varying light conditions on the system's reliability. In this study, logarithmic transformation and gamma transformation were used to compensate for too dark and too bright conditions respectively. Logarithmic transformation can expand the low gray value part of the image, showing more details of the low gray value part, and compress the high gray value part, reducing the details of the high gray value part, thereby emphasizing the low gray value of the image. part of the purpose, as in Eq. (1). Gamma transformation is mainly used for image correction, correcting images with too high gray or too low gray to enhance contrast, as in Eq. (2).

$$S = c \times log_{v+1}(1 + v \times r) \quad r \in [0, 1] \tag{1}$$

$$S = c \times r^{\gamma} \quad r \in [0, 1] \tag{2}$$

S is the output gray level of the pixel, c and γ are constants, r is the input gray level of the pixel, v is the logarithmic base.

This adjustment is aimed at enabling the Dlib module to acquire optimal facial recognition images, thereby enhancing the system's ability to accurately detect and track facial movements.

C. AI FACE FEATURE EXTRACTION

In this study, the process of detecting face landmarks in an image involves face detection and face landmarks, which are detected by using the Dlib's 68-point facial feature point detection model.

Dlib's 68-point facial feature point detection employs the HOG (Histogram of Oriented Gradients) and SVM (Support Vector Machine) methods to identify 68 facial feature points by analyzing facial characteristics and geometric shapes. HOG serves as a feature extraction technique that calculates the cumulative gradient intensity based on the gradient direction within a block, using this as the feature for the block. SVM, on the other hand, is a machine learning technology that seeks to find a hyperplane capable of accurately distinguishing between different categories of data. In summary, the HOG + SVM process involves extracting features from the image through HOG and subsequently using SVM to determine whether the features extracted from the image are present in the block.

In the HOG feature extraction process, the region of interest (ROI) is first cut out from the original image, and the ROI size is set to 64 × 128. The ROI can be represent as a coordinate (x, y, w, h), where x and y represent the coordinates of the upper-left corner, and w and h denote the width and height of the rectangle encompassing the face. Use two kernels g_x and g_y to calculate the Gradient in the x and y directions, as in Eq. (3), and find the intensity (g) and direction (θ) of each position as shown in Eq. (4) and (5). The gradient calculated in the x-direction will highlight longitudinal edges, the gradient calculated in the y-direction will highlight transverse edges, and the combined gradient strength will highlight all edges. Smoother areas will not be highlighted. Calculating gradients on an image can therefore highlight the contours and edges of the image.

In order to reduce noise interference and avoid being affected by a single pixel value, this study selected an 8 × 8 pixel unit block for analysis, captured image features and formed a feature vector. Divide the Gradient angle into 9 categories: 0, 20, 40, 60, …, 140, 160, etc., and then fill in the Gradient intensity of each pixel into the corresponding Gradient direction in the feature vector. Each cell has 9 bins. After calculating each cell (8 × 8 pixels), the sum of the gradient strengths in each gradient direction will be obtained. Since the calculation of Gradient is easily affected by the brightness of the image, the brighter the image, the greater the Gradient intensity. Therefore, normalization is needed to reduce the impact of image brightness. Using a block consisting of 4 cells for normalization, a 36 × 1 feature vector is obtained to represent the block. All these feature vectors are then concatenated together to form one large feature vector to represent that ROI. Therefore, the detected ROI is the face location.

Once the face location is determined, the next step involves establishing face landmarks using points within that rectangle. After having the feature vector, input the feature vector into SVM for training, and finally train an SVM model that can correctly judge faces.

$$g_x = [-1 \quad 0 \quad 1], \quad g_y = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \tag{3}$$

$$g = \sqrt{g_x^2 + g_y^2} \tag{4}$$

$$\theta = \tan^{-1}\left(\frac{g_y}{g_x}\right) \tag{5}$$

FIGURE 4. Dlib image recognition module [9].

Figure 4 displays a collection of 68 labeled facial points, each characterized by specific coordinates positioned around distinct facial features. The jawline point spans from 1 to 17, the right eyebrow point extends from 17 to 22, and the left

TABLE 1. Help and pointing commands table.

Mode	Command	Function
call-for-help mode	— — —	HELP~~~~~
	• • —	Thank you~~~~~
	— — • •	Change to pointing mode
pointing mode	• •	pointing function for moving forward
	— —	pointing function for moving backward
	— •	pointing function for Turn left
	• —	pointing function for Turn right
	—	Clear screen
	keep open mouth for 3 seconds	Exit and change to call-for-help mode

eyebrow point covers the range from 22 to 27. The sequence continues with the nose bridge point from 27 to 31, the lower nose point from 31 to 36, the right eye point from 36 to 42, the left eye point from 42 to 48, and the outer point of the mouth from 49 to 60. Lastly, the inner point of the mouth is indicated by the range from 61 to 68.

In the AI Face feature extraction component, the Dlib image recognition module (Figure 4) was utilized to detect the mouth and eye regions as the areas for autonomous movements.

While the mouth is in motion, the calculation of the distance (H) between point 62 and point 66, as defined in Eq. (6), will take place. Simultaneously, measuring the cycle time is defined as the duration from opening to closing the mouth movements for one complete cycle. Subsequently, these cycle times will be utilized to dynamically adjust the threshold for distinguishing between long and short durations through a fuzzy algorithm. if the cycle time is smaller than the threshold, it is categorized as short opening time (SOT), whereas a cycle time exceeding the threshold is classified as long opening time (LOT).

The movement is then encoded based on the interplay of long and short opening times. On the contrary, a short closing time signifies a command combination, while a long closing time indicates a command output.

$$\mathrm{H} = \sqrt{(P_{66x} - P_{62x})^2 + \left(P_{66y} - P_{62y}\right)^2} \tag{6}$$

D. FUZZY MOTION RECOGNITION ALGORITHM

The command combination in this system is controlled by the distance between P62 and P66, as well as the interval time of mouth opening and closing. A fuzzy logic controller (FLC) is a nonlinear controller that is easy to control and implement. It has better adaptability, robustness, and fault tolerance. It does not require any prior collection of a large amount of data for learning and training, and the calculation speed is very fast. To ensure stable command combinations, the system adjusts the time threshold for each individual's movements. A fuzzy motion recognition algorithm (FMRA) is employed in this study to improve the efficiency and accuracy of input by adjusting the time threshold. Figure 5 illustrates that '- -' indicates the time when the mouth is closed, while '–' represents the time when the mouth is open. The system combines the duration of the closing and opening time to generate command combinations. For example, if a long opening time is repeated three times, the system produces the "HELP" command and activates the alarm. If a short opening time is repeated twice and followed by a long opening time, the system outputs the "Thank you" command and turns off the alarm. This system can generate action commands as shown in Table 1, and the command functions can be expanded to meet the user's requirements.

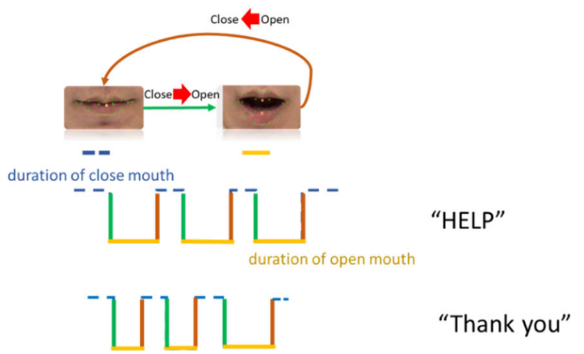


FIGURE 5. Schematic diagram of continuous mouth movements.

The FMRA [9], [19], [20], [21] describes as follows:

The block diagram of the fuzzy motion recognition algorithm is shown in Figure 6.

To find a stable typing speed, the raw input signal *I(k)* is normalized through the function NL,

$$NL \begin{cases} X(k) = I(k), & \text{if } I(k) < threshold_k \\ X(k) = \frac{l}{3} I(k), & \text{if } I(k) \geq threshold_k \end{cases} \tag{7}$$

For the kth frame, $X(k)$, the prediction error e_k of a fuzzy algorithm is estimated as

$$e_k = \frac{X(k) - Y(k-1)}{L}, \tag{8}$$

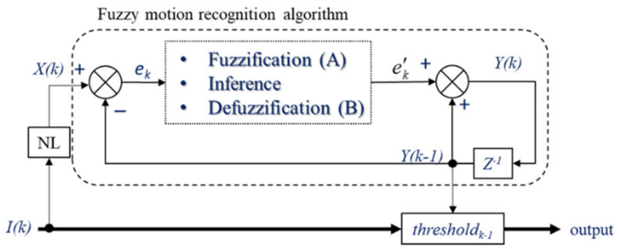


FIGURE 6. The structure of FMRA. The variable z^{-1} is a unit delay for the next step.

where *Y(k-1)* is the threshold at the k-1 frame. The initial threshold value, *Y(0)*, is predefined, it can be estimated using the average power energy of the first M-frames; L is the error tolerance range, which we define as 100ms, when e_k is large than 1 or smaller than -1, thus e_k is 1 or -1, respectively.

Because the Mamdani inference model [9] combines the sets and rules for fast and simple calculation, it is selected with linguistic rules for defining the relation between the input and the output. The fuzzy sets A and B are used in the fuzzification and defuzzification process. The input range of the fuzzifier and the output range of the defuzzifier are from -1 to 1. Considering the performance and stability of a recognition algorithm, the number of fuzzy sets is five. The linguistic parameters of these five fuzzy sets are negative large (LN), negative small (SN), zero (ZE), positive small (SP), and positive large (LP). The fuzzifier ranges from A_1 to A_5 where A_1 is LN, A_2 is SN, A_3 is ZE, A_4 is SP, and A_5 is LP. The range of the defuzzifier is from B_1 to B_5 where B_1 is LN, B_2 is SN, B_3 is ZE, B_4 is SP, and B_5 is LP. According to the fuzzy set calculations, the fuzzy inference rules are as follows.

$$\text{If } e_i \text{ is }_{\mathrm{Ai}} \text{ then } e'_i \textit{ is } B_i, \quad i = 1, 2, \ldots, 5, \tag{9}$$

where e_i is the input variable of fuzzifier in the fuzzy sets A and e'_i is the output variable of defuzzifier in the fuzzy sets B.

A defuzzification process is then used to obtain a finite number as an output. In this study, using the center of gravity method, the output variable, e'_k, of fuzzy threshold can be calculated following

$$e'_k = \frac{\sum_{i=1}^{n} S_i\left(e_k\right) B_i\left(e_k\right)}{\sum_{i=1}^{n} S_i\left(e_k\right)} \tag{10}$$

where S_i is the membership grade of the i*th* premise in the inference rule, and B_i is the central value of the i*th* conclusion in the inference rule.

The threshold value is then updated by

$$Y(k) = Y(k-1) + e'_k \times L, \tag{11}$$

$$threshold_k = Y(k) \times 2. \tag{12}$$

Finally, the output is 1 which represents LOT, if I(k) $\geqq$ $threshold_{k-1}$; otherwise, the output is 0 which represents SOT.

E. CLINICAL APPLICATION DESIGN

In this study, the commands for an emergency assistance function for patients with severe physical disabilities are designed, which include calling for help and pointing. These functions can be activated by inputting a control command signal as shown in Table 1, where '–' represents LOT, which stands for 1, and '•' represents SOT which stands for 0. When the NCEA system is activated, it enters the call-for-help mode. If the user is using a wheelchair and wishes to indicate the direction of movement, they can enter the mode switching code (––••) to switch to the pointing mode and select a direction. To switch back to the call-for-help mode, the user simply needs to open their mouth for three seconds, and the system will automatically revert to the call-for-help mode. The command set utilized in this study is merely an illustrative example, with the current implementation employing up to four bits to validate the research methodology. Subsequent researchers can devise their own set of instructions, drawing upon this as a basis for their own studies. For instance, employing N bits allows for the control of 2^N types of commands/messages.

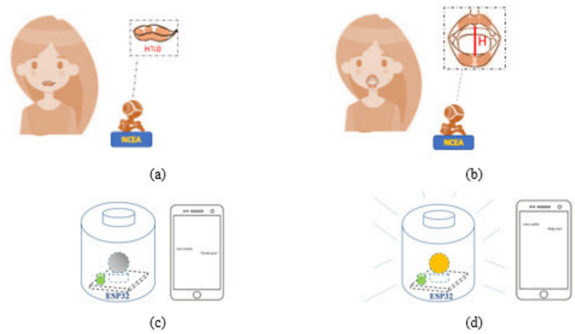


FIGURE 7. The operation method of NCEA is through mouth movements: (a) closed mouth state, (b) open mouth state, (c) release alarm status, (d) alarm status.

In clinical applications, the system can be operated in two ways. Generally, users can input actions using their mouths or eyes through image sensors. For instance, as depicted in Figure 7, when a user closes their mouth, the distance between their two lips approaches 0, while when they open their mouth, the distance between the two lips is greater than 0. Since everyone has different movement habits, a threshold value (e.g., H>5 pixels for open mouth (Figure 7(b)) and close mouth (Figure 7(a))) must be set to recognize the current mouth status and activate the timing for this state. When the status changes, the timing of the previous state stops, and the timing of the current state begins. Then, the command combination is determined based on the duration of the mouth status and the number of changes, and so on continuously. Once the action command is confirmed, the alarm device will be triggered (Figure 7(d)) or stopped (Figure 7(c)), and a message will be sent to a smartphone or computer.

The NCEA system can be installed next to the bed, with a webcam positioned at one end of the bed as shown in Figure 8. The webcam should be placed to ensure clear identification of human faces. Multiple alarm devices with Wi-Fi signals can be installed anywhere, such as in different corners of the home, office, or on another floor.

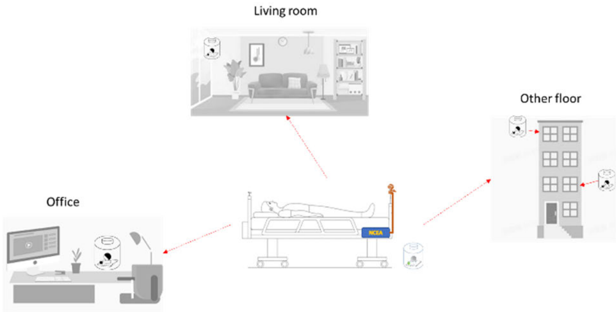


FIGURE 8. NCEA system is installed beside the patient, alarm device can be installed anywhere.

FIGURE 9. NCEA system installed on a wheelchair.

While on outings, the NCEA system can be mounted on a wheelchair, as depicted in Figure 9. Caregivers can receive directional messages on their smartphones or OLED screens from the disabled who cannot speak. Users can actively point out the direction they want to move through the NCEA system instead of letting the caregiver push it.

III. RESULTS

The NCEA system designed in this study can be installed and run on an embedded system, as illustrated in Figure 10, the NCEA system components include a Raspberry Pi 4 (OS 64bit), an adjustable stand, a pumpkin-shaped alarm device, and a display screen, as shown in Figure 10(a). The display screen is used for system function confirmation and is not necessary for actual system use. During image recognition, the system displays feature points, such as the mouth contour, eyebrows, and left eye, to capture and recognize actions. The alarm circuit includes a button switch, an OLED screen, a speaker, a photo-resistor, and a microprocessor ESP32 board, as depicted in Figure 10(b). Figure 10(c) shows the front of the alarm device shaped like a Moai statue, while Figure 10(d) shows its back.

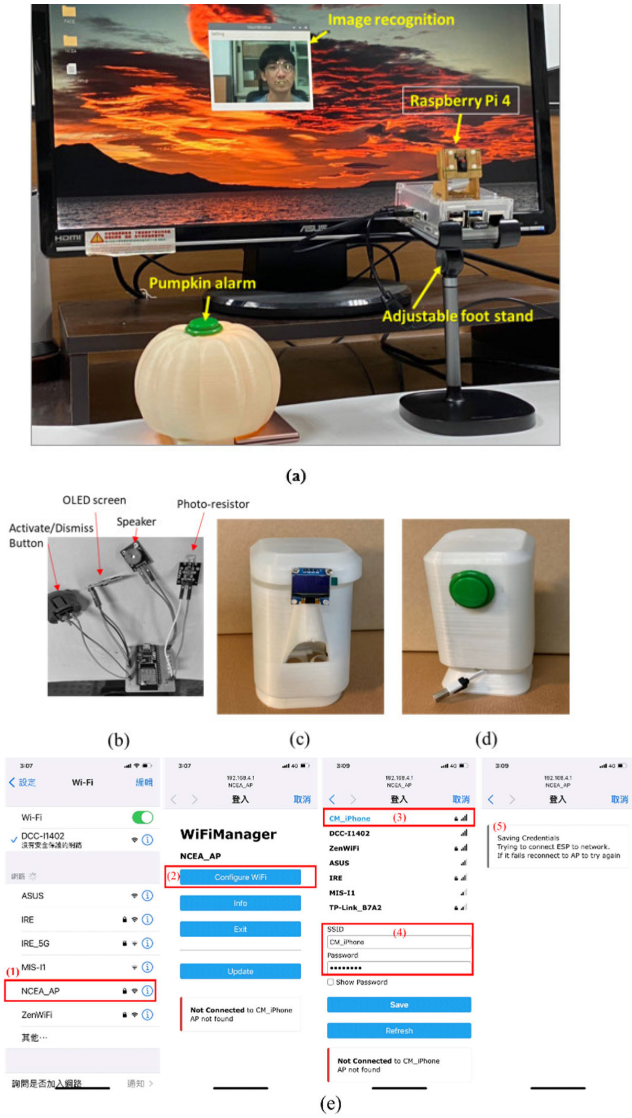
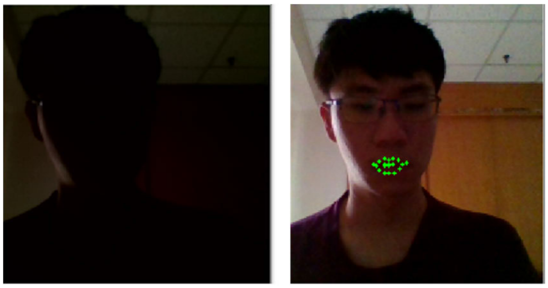


FIGURE 10. The NCEA system consists of (a) the components of the NCEA system, (b) the alarm circuit, (c) the front of the alarm device, (d) the back of the alarm device, and (e) alarm device setup steps.

The installation process of the NCEA system is simple, the NCEA software will be integrated into the Raspberry Pi and will initiate automatically upon startup. The alarm device necessitates local network setup by cell phone or personal computer only during its initial usage, the default SSID of the alarm device is ''NCEA_AP'' as Figure 10(e), thereafter conveniently functioning by directly connecting to the USB socket.

A. COMPENSATION OF THE NCEA SYSTEM

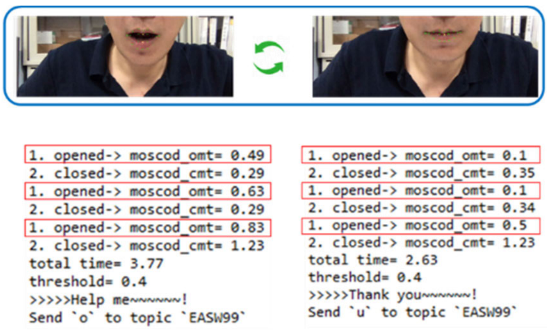
The image compensation performance of the NECA system is shown in Figure 11. Figure 11(a) is a state without light. The Dlib module cannot capture facial features. After the system light compensation calculation, Figure 11(b) can increase the image brightness. Allows the Dlib module to function



(a) (b)

FIGURE 11. The image compensation performance of the NECA system (a) before compensation, (b) after compensation.

properly, so the NCEA system can work normally even at night.



(a) (b)

FIGURE 12. The NCEA system operation, (a) activates the alarm system, (b) is deactivated.

B. TO OPERATE THE NCEA SYSTEM

The operation of activating and deactivating the alarm is illustrated in Figure 12, where opening and closing the mouth represent a cycle of inputting action commands. In Figure 12(a), opening the mouth for more than 0.4 seconds three times can trigger the alarm system and send the command 'o' to activate the alarm light through MQTT. In Figure 12(b), opening the mouth twice for less than 0.4 seconds and once for more than 0.4 seconds can stop the alarm system and send the command 'u' to turn off the alarm light through MQTT. The output status of the NCEA system is presented in Figure 13. When the alarm system is triggered, a 'HELP' message will be sent to LINE notify, and the alarm light and speaker will be activated. When the alarm system is stopped, a 'Thank you' message will be sent to LINE notify, and the alarm light and speaker will be turned off.

C. PARTICIPANTS

The study encompassed 12 participants, consisting of eight males and four females, aged between 20 and 63 years. Among them, one participant had a spinal cord injury, another had cerebral palsy, and the remaining participants were considered normal, displaying typical mouth movement function. Within the male cohort, seven were novices aged between 20 and 30, while the eighth (S8) was a 50-year-old male with cerebral palsy, exhibiting normal brain function but with diminished mouth movement capabilities. The Morse Code Translator (MCT) [17] was employed to facilitate input. Furthermore, the research featured four female participants, with three being novices aged between 20 and 30, and the fourth (S12) being a 63-year-old individual with an upper C3-C4 spinal cord injury. This participant demonstrated normal brain function and exhibited typical mouth movement function. Additionally, she had experience using MCT for translation.

FIGURE 13. The NCEA system outputs status, with alarm status on the left and alarm release status on the right.

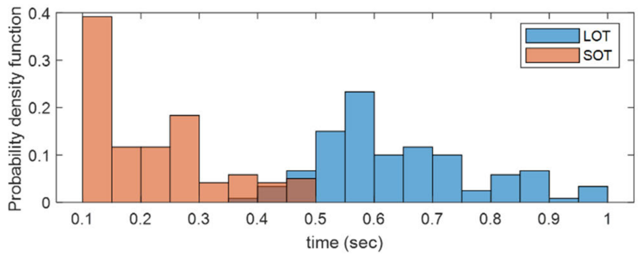


FIGURE 14. The probability density function histogram of LOT and SOT data.

D. THE PERFORMANCE TEST OF FMRA

Due to individual variations in the ability to control mouth closure, even the same person may demonstrate different levels of control over time. Participants were instructed to perform rapid and slow mouth opening and closing movements, each repeated ten times, with the measurement of cycle time. The underlying distribution of LOT and SOT data is illustrated in Figure 14. It can be observed that the basic distribution of LOT and SOT data carries the risk of misjudgment between 350 and 500 milliseconds. To enhance the stability of real-time NCEA systems, this study proposes using FMRA to adjust the thresholds for LOT and SOT. Its advantage lies in the ability to rapidly adapt the threshold based on the operator's input speed, without the need for pre-learning extensive data. Sudden changes in typing patterns are common among individuals with disabilities, particularly those with cerebral palsy. Recognition systems must demonstrate the ability to adapt to chaotic conditions. In Figure 15, variations in typing speed are simulated using a stable sinusoidal input pattern. Two random typing areas, denoted as (I) and (II), are introduced to assess the recovery capabilities of the fuzzy recognition system. The amplitude of the sinusoidal analog data is set to 500 millivolts, with a sampling rate of 10Hz, and one cycle is 2π seconds. As a result, the system exhibits the capacity to promptly recover its recognition function from a chaotic state. Additionally, it was observed that the prediction threshold (depicted by the dashed line) in the random typing region can be rapidly adjusted.

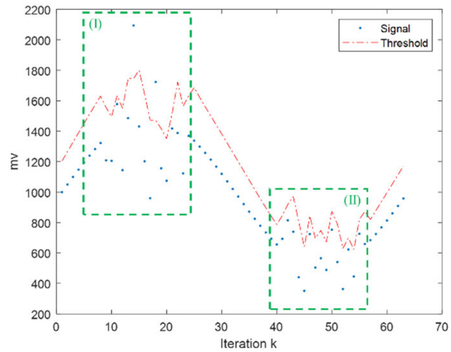


FIGURE 15. **Typing speed simulation with fuzzy recognizer.**

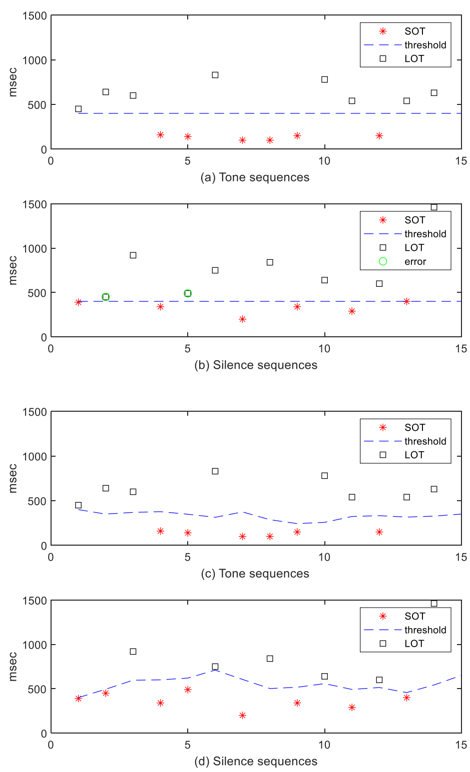


FIGURE 16. **The recognition performance tests, (a) and (b) recognize the tone/silence sequences by the fixed threshold, and (c) and (d) recognize the tone/silence sequences by the FMRA.**

To substantiate the effectiveness of FMRA, participants were assigned the task of entering a sequence comprising 28 Morse code characters, with a specific focus on maintaining continuity for six characters: 'o, u, i, a, n, m.' The input time for each character was meticulously recorded. Subsequently, judgments for LOT and SOT were made using a fixed threshold of 400 milliseconds (see Figures 16(a) and (b)), alongside an assessment of the adaptive threshold employed by FMRA. The initial judgment thresholds for LOT and SOT were also set at 400 milliseconds (see Figures 16(c) and (d)). A noteworthy observation emerged: when confronted with varying input speeds from users, the fixed threshold for silence in Figure 16(b) resulted in two recognition errors (indicated by green circles). In contrast, FMRA, with its ability to fine-tune thresholds, demonstrated accurate recognition in this specific environment. In Figure 16, the symbols '*' represent SOT, '□' represents LOT, '◯' denotes recognition errors, and the dashed line indicates the Morse code recognition threshold.

E. THE OPERATION PERFORMANCE TEST OF NCEA

In this study, NCEA system performance was tested on twelve participants. Each participant performed a test consisting of 6 instructions, inputting each instruction 5 times, twice a week for 4 weeks. The completion time of instruction input was recorded, and the mean accuracy was calculated as Figure 17. The average accuracies of inputs from 12 participants are 89.19%, 96.69%, and 100% for the first, third, and sixth trials, respectively. Therefore, a participant can easily use the device after a training process.

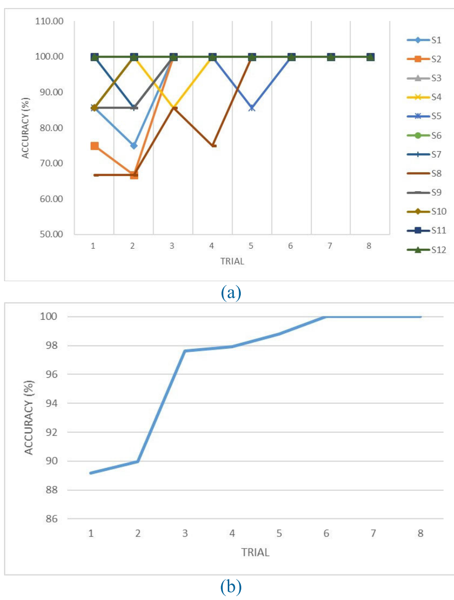


FIGURE 17. **The (a) individual and (b) average accuracy of inputs from twelve participants.**

Using the alarm command as an illustration, the average input time for the command (– – –) among twelve participants ranged from 3.7 seconds as the fastest to 6.7 seconds as the slowest. On average, it took approximately 4.25 seconds to complete an alarm command.

FIGURE 18. The NCEA system is installed in the participant's home.

FIGURE 19. The participant activates the alarm by operating the NCEA system.

F. CASE STUDY

The case study participant is a 50-year-old male (Hong) who has congenital infantile paralysis, which has resulted in his inability to move his limbs independently and a high level of muscle tone. The NCEA system has been provided to the participant, and the equipment has been installed on the third floor of the case home according to the diagram at the bottom left of Figure 19, another alarm device was put on the first floor. Figure 19 depicts the patient actually operating the NCEA system to activate the alarm. Opening the mouth is shown in Figure 19(a), (c), and (e) while closing the mouth is shown in Figure 19(b), (d), and (f).

After using the NCEA system for one month, we asked Hong and his father (primary caregiver) to complete the Table 2 questionnaire. This study used QUEST 2.0 [22] to conduct a satisfaction survey on individual cases. The QUEST 2.0 scale is used to assess satisfaction with a specific assistive device and has 12 items; eight of the items assess the characteristics of the assistive device in terms of: size (dimensions), weight, adjustment, safety, durability, ease of use performance, comfort and effectiveness. The remaining four items assess service and include: service delivery, repairs and service of the device, professionalism of service and follow-up service. However, we will ignore the above four items in this study.

TABLE 2. Quebec user evaluation of satisfaction with assistive technology.

Assistive Device	Hong	Father
1. How satisfied are you with the dimensions (size, height, length, width) of your assistive device?	5	5
2. How satisfied are you with the weight of your assistive device?	NA	5
3. How satisfied are you with the ease in adjusting (fixing, fastening) the parts of your assistive device?	NA	5
4. How safe and secure your assistive device is?	5	5
5. How satisfied are you with the durability (endurance, resistance to wear) of your assistive device?	5	5
6. How easy it is to use your assistive device?	4	NA
7. How comfortable your assistive device is?	5	NA
8. How effective your assistive device is (the degree to which your device meets your needs)?	5	NA

Item scores are: 1 = not satisfied at all, 2 = not very satisfied, 3 = more or less satisfied, 4 = quite satisfied, 5 = very satisfied.
NA (non-applicable) was used for items in which Lisa or her father could not answer (i.e., Lisa regarding the weight of the device).

Participants are asked to rate their satisfaction for the device on a five-point scale that ranges from "not satisfied" at all to "very satisfied." Finally, participants are asked to choose the three most important items related to the assistive device in question. Table 2 reports the results of QUEST 2.0. Even though other improvements may be made in the future, Hong and his father are generally pleased with NCEA's features. In particular, Hong gave the device the highest possible score (5) for its effectiveness; he found the NCEA to be a good fit for his help-seeking needs.

After the case test, both the patient and family members indicated that the non-contact image switch used in this study enabled the patient to easily operate the system and actively seek help from others. This greatly reduced the psychological

TABLE 3. Comparison of the features with traditional call bells.

Type	Trigger alarm method	Trigger type	Interaction	Ability	Suitable
Push-button call bells	Press button	Active	contact	movable parts of the body	General patients
Wireless remote control call bells	Remote control button	Active	contact	movable parts of the body	General patients
Sound sensor call bells	Sensor sound	Active	contactless	movable parts of the body	General patients or quadriplegia with voice ability
Voice control call bells	Voice commands	Active	contactless	voice	General patients or quadriplegia with speech ability
Pressure-sensitive call bells	Change pressure	Passive	contact	movable parts of the body	General patients
Smart call bells	Smartphone apps	Active	contact	hand function is normal	General patients
Wearable call bells	Changes in physiological signals	Passive	contact	none	General patients, quadriplegia
NCEA	Image action	Active	contactless	Mouth opens and closes normally	General patients, or quadriplegia without voice ability

burden and caregiver time for the family or caregiver, who no longer needed to be on standby all the time.

IV. DISCUSSION AND CONCLUSION

The main purpose of this study is to develop a practical contactless emergency alert system for people with severe physical disabilities. This research successfully applied artificial intelligence image processing and fuzzy motion recognition technology to convert image motion characteristics into command signals, and combined it with Internet of Things technology to establish a set of one-to-many call bells, successfully solving the problem of help for patients with quadriplegia. It provides a unique alternative to commercially available call bells that are operated manually or via voice commands. Table 3 lists a feature comparison with traditional call bells. In Table 3, most devices associated with traditional call bells typically require hand activation. Voice instructions may be suitable for some paralyzed patients with speech ability, while patients without voice ability can choose to use the NCEA system developed in this study.

In terms of system performance, traditional image recognition is easily affected by factors such as ambient lighting conditions. The NCEA system uses the compensation function provided by OpenCV to mitigate the impact of lighting and reduce the instability caused by different lighting conditions on system reliability. The Fuzzy Motion Recognition Algorithm (FMRA) effectively improves typing speed instability, quickly corrects manual input, and enhances system robustness. After a series of system optimizations, experimental results show that the system is highly user-friendly and easy to learn. The accuracy of novices operating the NCEA system is approximately 96.69%. Study participants and their families found the device useful, allowing users to request help and live independently, thereby reducing psychological stress and workload for family members and caregivers.

Regarding the participants, the experimental results (Figure 17) found that the difference in mouth movement control ability between spinal cord injury patients and person without disability was very small. Surprisingly, spinal cord injury patients outperformed beginners, possibly attributed to the participants' prior experience with Morse code input. It's important to note that reaction times may slightly vary among individuals due to differences in mouth abilities. Specifically, individuals with cerebral palsy, characterized by poor mouth movement abilities, exhibited a relatively unstable system performance. Nevertheless, through repeated practice, participants overcame these challenges, showcasing their ability to actively control the system despite physical limitations.

NCEA system is a one-to-many alarm system, it can establish a safety net easily; the alarm device can be placed anywhere in the home or any building with a network according to specific needs. When the alarm is triggered, all alarm devices are activated simultaneously, ensuring that all family members or caregivers can promptly receive the alarm message and take immediate action to prevent accidents. Disarming the alarms requires only one person (e.g., a caregiver, where "caregiver" is just one example) to press the alarm disarm button. Therefore, the NCEA system is simple to operate, suitable for a variety of patients, and scalable and convenient.

All in all, this study successfully developed an emergency assistance system (NCEA) controllable by quadriplegic patients, through the NCEA system, quadriplegic patients have overcome the operational limitations of commercially available call bells and can actively express their needs at any time. Build a safety net for quadriplegic patients, family members and caregivers do not need to be around to take care of them all the time, which greatly improves their quality of life.

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