Human–machine interface-based wheelchair control using piezoelectric sensors based on face and tongue movements

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Abstract

Hand-free control of assistive mobility devices has been developed to serve people with movement disabilities at all levels. In this study, we demonstrate a human–machine interface (HMI) system that uses piezoelectric sensors to translate face and tongue movements. This study addresses two issues. First, we used six piezoelectric sensors to acquire muscular facial signals to observe the sensor positions and features during winking and tongue movements. Second, we verified the proposed HMI for online simulated wheelchair control. Twelve volunteers participated in the experiment. A maximum classification accuracy of 98.0% from the maximum and mean parameters could be achieved using the linear discriminant analysis and K-nearest neighbors classification algorithms. Using the proposed algorithm, command translation patterns for command translation reached more than 95% of the average classification accuracy with 0.5 s of the window for command creation. For online control of the simulated wheelchair, the results showed high efficiency based on the time condition. The combination of winking and tongue actions results in a steering time of the same magnitude as that of joystick-based control, which is less than twice the time of a joystick. Hence, the proposed system can be further implemented in a powered wheelchair for quadriplegic patients who retain control in the face or tongue muscles.

1. Introduction

Assistive technology refers to any device or system that supports people with disabilities or older people in performing daily activities independently or with assistance [1, 2, 3]. Many researchers aim to invent and develop assistive, adaptive, and rehabilitative devices [3, 4, 5]. The human–machine interface (HMI) [6, 7, 8] is one method that can be applied to produce and evaluate an assistive device or a system. For practical use in severe disabilities, we have mainly developed assistive, adaptive, and rehabilitative devices by employing biomedical signals and physical signs. Examples of commercial HMI systems to support people with movement disabilities in their daily activities include voice recognition [9, 10], Sip and Puff switch using air pressure from lungs [11], Chin switch [12], and head pointer [13, 14, 15], which employ head–neck movements and eye trackers using cameras to detect pupil movement and direction [16]. However, an HMI system that covers all levels of disability still needs to be developed. The use of biomedical signals for HMI systems is an alternative approach, such as an electromyogram (EMG)-based HMI system for controlling electric devices or powered wheelchairs [17, 18, 19, 20]. A facial EMG signal measures biopotential changes when facial, jaw, and tongue movements are executed. Electrooculography (EOG) measures biopotential changes during eye movements, such as winking and blinking [21]. A face–machine interface based on EMG and EOG signals has been proposed [22]. In addition, a tongue–machine interface was developed for practical wheelchair control [23]. Both modalities can provide highly efficient mobility enhancement [24]. In addition, a brain–computer interface (BCI) is an excellent technology that directly connects the brain and a computer or machine through brain signals or electroencephalogram (EEG) [4, 25, 26]. The BCI system requires a long training time and skills for EEG device installation. However, BCIs are beneficial for quadriplegic or severely paralyzed patients. Moreover, a multimodal control technique cooperating with an intelligent machine was proposed to cover various levels of disabilities that improve conventional HMI systems [27, 28].

Currently, HMI research is focused on design and development based on usability, flexibility, and economy. For example, low-cost amplifiers with wireless modules and electrodes have been reviewed for prototyping applications. Based on a previous study, EEG artifacts from a neuroheadset were proposed for face–machine interface [29]. In addition to using biomedical signals, research on tongue–machine interfaces has
been conducted using different sensors, such as magneto-inductive sensors [30] and force sensors [31], to capture tongue positions and movements.

Previous studies have reported that tongue movements exhibit quick control responses. However, the user may be uncomfortable while some materials or devices are in the mouth. Therefore, in this study, we aim to develop a practical HMI system to control an electric wheelchair for quadriplegic patients by utilizing facial and tongue movements. A piezoelectric sensor is a converter that changes mechanical power, that is, pressure, acceleration, temperature, strain, or force, to electrical power based on the piezoelectric effect. It has been utilized in various applications, such as in the medical, aerospace, and instrumentation fields. A thin-film piezoelectric sensor was used to measure and record muscle activity [32]. Hence, it is necessary to observe the possibility of using piezoelectric sensors to capture facial muscles. Moreover, we designed control creation and translation for HMI-based simulated wheelchair control. The efficiency of the proposed HMI system was verified through offline and online testing. The remainder of this paper is organized as follows. In Section II the research methods, including the proposed system, signal acquisition and processing, feature extraction and algorithms, and command translations are discussed. Section III presents the experimental results and discussion to verify the efficiency of the offline testing. The online testing is presented in Section IV. In Section V, the outcome and future work of the proposed system are presented as conclusion and future work.

2. Proposed methods

In this work, we focus on connecting a human to a machine through face and tongue movements using piezoelectric sensors for practical machine control. The study starts with using piezoelectric sensors to acquire and measure facial muscle actions for the HMI system. Feature extraction and classification methods were observed in the next step. Next, we prototyped and verified the efficiency of the proposed HMI system for wheelchair control. All the processes involved in the study as shown in Figure 1.

2.1. Proposed HMI system based on facial muscle using piezoelectric sensors

For practical machine control, we focus on connecting a human to a machine through face and tongue movements using piezoelectric sensors. We prototyped and verified the efficiency of the proposed HMI system for wheelchair control. An overview of the proposed system for simulated wheelchair control is shown in Figure 2. The process consists of three main parts. The first is signal acquisition, which involves two procedures: detection of facial muscle movements with a piezoelectric sensor and conversion of analog signals to digital signals. The second part is signal processing, and the algorithm includes: a signal segmentation process, feature extraction process resulting in highlighting the important data, and classification. Finally, the classification result was used for command translation to create commands for several applications.

2.2. Signal acquisition

For non-invasive EMG signal acquisition [33], electrodes are placed on the skin over the measured muscle. This requires two or three electrodes for a single EMG channel. In this study, we employed a thin-film piezoelectric sensor to acquire facial muscle activity from facial and tongue movements. The thin-film type is used in applications with high frequency and small size. A piezoelectric sensor is simple and ready for
immediate use, proportional to the level of muscular contraction, non-invasive, non-obstructive, easy to wear, resilient, unaffected by electromagnetic interference, and inexpensive [34, 35]. The sensor was mounted along the contours of the face. For the six channels of facial muscle signal acquisition, we placed six thin-film piezoelectric sensors on the user’s face and put a medical masking tape over and under to prevent the sensors from directly contacting the skin, as shown in Figure 4(a). Four sensors (S1, S2, S3, and S4) were set around the lips to detect tongue movement and two sensors (S5 and S6) under the eyes to detect eye blinking action.

2.3. Operation of piezoelectric sensors

A piezoelectric sensor can convert physical quantity, i.e., acceleration, strain, force, or pressure, into electrical signals without an external power supply. A thin film piezoelectric sensor is highly sensitive and very small and is used in high-frequency applications [34]. The operation of piezoelectric sensors to measure facial muscle actions is shown in Figure 3(a). The components consist of thin film piezoelectric sensors, an analog-to-digital (A/D) converter, and a computer with measuring software. The piezoelectric sensor can generate an analog signal when

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**Figure 3.** (a) Diagram of operation of a piezoelectric sensor (b) the components of using a piezoelectric sensor for measuring facial muscle actions.

**Figure 4.** (a) Placement of six thin-film piezoelectric sensors. (b) Example of the signal while sensor S1 was activated by left eye winking. (c) Example of the piezoelectric signal of sensor S3 generated by pushing the tongue on the upper left lip.
receiving some force from facial muscle action. The analog signals are sent to the A/D converter to transform into digital signals for recording in a computer.

The DT-0524 piezoelectric sensor (https://www.farnell.com/data sheets/2310782.pdf) can generate output voltages ranging from 10 mV to 100 V. Hence, it can be connected directly to an analog input pin of USB-6009 multifunction I/O device without an amplifier for analog-to-digital conversion, and it is able to send the digital signal to the computer. Figure 3(b) shows the connection diagram of the components for signal acquisition. The sampling rate was 2000 Hz. Six-channel signals were processed and recorded in LabVIEW. The six proposed commands arranged six actions of tongue movement and eyewink for activating each sensor target mentioned in Table 1. The observation of the signal feature in Figure 4(c) shows an example of the signal acquired from target sensor S1, which is activated by eye winking. Figure 4(c) shows an example signal generated by tongue movement with the target sensor at S3.

All the participants provided written informed consent. Before signing, they received and read the protocol documents to participate in the study. All signed consent forms (without personal identification) were kept confidential. All protocols involving human participants were approved by the Office of the Human Research Ethics Committee of Walailak University (Protocol code: WU-EC-IN-1-404-64), which adopted the Ethical Declarations of Helsinki, Council for International Organizations of Medical Sciences (CIOMS), and the World Health Organization (WHO) guidelines.

2.4. Feature extractions

In this study, we examine the use of piezoelectric sensors for physiological signals. The characteristics of the recorded muscle signals from the piezoelectric sensors (Figure 3(b) and (c)) are similar to those of the EMG signals. Hence, we employed conventional feature extraction techniques for EMG to implement the proposed muscle-acquisition techniques. Three methods are used following the research survey on using EMG for machine control [36, 37]: time-domain (TD) features, frequency domain (FD) features, and time–frequency domain (TFD). We used TD methods for preliminary testing of a simple technique with low complexity to reduce noise and highlight the essential data for parameter setting. Before extraction, the amplitude of all recorded signals was adjusted to the range [−1,1] by min–max normalization for rescaling. Five features, including maximum peak value (MAX), mean value (MEAN), standard deviation (STD), summation (SUM), and root mean square (RMS), were extracted from the rescaled signals. We observed the efficiency of each feature by using conventional classification techniques. All selected features can be calculated as following Eqs. (1), (2), (3), (4), and (5):

1) Maximum Peak Value (MAX):
   
   \[ MAX = \text{Max}(x_i) \]  

2) Mean Value (MEAN):
   
   \[ \text{MEAN} = \frac{1}{n} \left( \sum_{i=1}^{n} x_i \right) \]  

3) Standard Deviation (STD):
   
   \[ \text{STD} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n-1}} \]  

4) Summation (SUM):
   
   \[ \text{SUM} = \sum_{i=1}^{n} x_i \]  

5) Root Mean Square (RMS):
   
   \[ \text{RMS} = \sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}} \]  

where \( n \) is number of values in data set, \( s \) is data set of signal acquisition in each sensor, \( x_i \) is the value at element \( i \) in data set, \( \sum_{i=1}^{n} \) is a function that returns the summation of the first element to the element \( n \) in data set, \( \bar{x} \) is sum of values (all element) of a data set divided by number of values.

2.5. Classification methods

The proposed system generates six commands for wheelchair steering. After preprocessing and feature extraction, feature parameters were provided for six-class classification. We utilized a different classifier technique [38] that is used for EMG-based HMI [36, 37], as follows:

1) Linear discriminant analysis (LDA) is commonly used to classify patterns into two or more categories. LDA assumes that all classes are linearly separable, and numerous linear discrimination functions representing several hyperplanes in the feature space are generated to identify classes.
2) K-nearest neighbors (KNN) are a supervised learning classifier that uses similarity to classify or predict a dataset. The KNN is a simple approach for signal and pattern recognition in several applications.
3) The support vector machine (SVM) is an unsupervised learning classifier that uses machine learning theory to maximize the predicted accuracy while avoiding overfitting data for classification and regression prediction.
4) An artificial neural network (ANN) is a computational model based on brain and nervous system studies. The connections between neurons are modeled in the ANN as the associated weight and threshold between the node layers for activating and sending data. ANNs can be used for predictive modeling, adaptive control, and applications, where they can be trained using a dataset to understand sensory inputs and categorize or cluster raw data. For example, images, sound, text, data, and biomedical signals must be translated into the patterns that they recognize: numerical and encoded in vectors.

3. Experimental results

Twelve healthy volunteers (six females and six males, with an average age of 20.68 ± 0.9 years) participated in the experiments. For signal recording, we had to prepare participants for their faces to reduce oiliness and install six piezoelectric sensors, as shown in Figure 4(a). For one session, we requested the participants to perform ten times per command.
According to the actions in Table 1, the LabVIEW program (ver. 2012 SP1) was used to record signals from the piezoelectric sensors for 4 s every time an action was performed (8000 data samples). The participants had 1 min to rest before moving to the next command. Each participant performed four sessions 40 times per command.

According to the example of raw signals in Figure 4(b), we can calculate as follows Eqs. (1), (2), (3), (4), and (5) to obtain the data of the selected features. Figure 5 shows an example of the raw data of the selected features from the signal while winking the left eye, which is target sensor number 1 (S1). We visualized that the highest value of each selected feature was provided by S1, and other target sensors also showed. After preprocessing and feature extraction for data collection using LabVIEW program, the datasets of each feature parameter were classified by using Classification Learner app based on MATLAB (ver. R2021b). It is a standard library that provides several classification algorithms as we mention in Section 2.4. It turns relevant parameter of each algorithm automatically based on training set and target results. For instance, the weight and threshold of ANN were randomly set at first and they would be adjusted aligned with the training set to get the best prediction. In addition, it provided learning techniques to avoid overfitting such as a cross-validation setting. The suitable algorithm, reaching the highest accuracy, could be employed for an online HMI system, as described in the next section. We employ the accuracy of model prediction as an evaluation classification model as follows Eq. (6):

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}
\]

A true positive (TP) is a result that came out as expected. True negatives (TN) are an accurate outcome of an unanticipated undesirable result. A false positive (FP) is an incorrect result that was predicted. False negative (FN) results are actual findings that were not anticipated. All values were collected from the confusion matrix which automatically produce by the Classification Learner App.

Figure 6 illustrates the evaluation of the proposed features and classification methods. The average classification accuracy ranges from 86.0% to 98.0%. We observed that a maximum classification accuracy of 98.0% from the maximum (MAX) and mean (MEAN) parameters could be achieved using the LDA and KNN classifiers. Moreover, standard deviation (STD) features revealed a lower average classification accuracy than other features. For classification methods, LDA and KNN classifiers achieved classification accuracies ranging from 93.0% to 98.0%, whereas SVM and ANN had lower accuracies.

Figure 5. Example of the raw data of the selected features from target sensor number 1 (S1) from winking the left eye action.

Figure 6. Results of the proposed features and classification methods.
Moreover, we employed machine learning (ML) classification metrics that are precision [39], recall, and F-measure to evaluate model performance. Precision is a probability of correctly predicted actions against total predicted actions from classification algorithms; recall is a probability of correctly predicted actions against actual actions from classification algorithms; F-measure is a balanced point between precision and recall. Each of the measurement metrics can be considered as following Eqs. (7), (8), and (9):

\[
\text{Precision (PS)} = \frac{TP}{TP + FP} \quad (7)
\]

\[
\text{Recall (RC)} = \frac{TP}{TP + FN} \quad (8)
\]

\[
F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (9)
\]

All measurement parameters were collected from the confusion matrix automatically generated from the Classification Learner app as shown in Table 2.

Table 2 shows model effectiveness based on PS, RC, and F1 given relevant features that are MAX, MEAN, RMS, STD, and SUM. The results highlight that they could help model predict the actions acceptably, which reached over 90%. However, F1 of STD was quite low because our ANN achieved over 95%. Moreover, LDA and KNN produced low FT and lower performance.

In the term of model performance, the F1 scores of LDA, SVM, and KNN achieved over 95%. However, LDA and KNN produced low FT and FN according to the scores based on PS and RC. However, the ANN model got the lowest performance even though it is a well-known algorithm that is suitable for predicted systems, it could not convert the weight and bias to correct co-efficiencies in our cause study. This is because we employ few input features that ANN needs good-enough training data (60 cases per subject). This suggests that they are highly potential to apply our proposed model to the suggested HMI system in the online part.

Next, we proposed a real-time HMI system by covert the command for direction control of the simulated wheelchair. Because of the high accuracy of the MAX feature, KNN and LDA were the high classification efficiency. In the preliminary testing of real-time HMI, we selected the MAX feature and LDA classifier were for command creation.

4. Proposed Human–Machine interface system using piezoelectric sensors for simulated wheelchair control

This section presents the proposed online HMI system that uses piezoelectric sensors for simulated wheelchair control. We prototyped an HMI system and tested it using McGill immersive wheelchair simulator (miWE) [39, 40]. In Section III, we selected the maximum peak (MAX) feature with a linear classifier as a simple algorithm to automatically generate commands and calculate the resulting accuracy rates for a preliminary test in real-time processing. The experiments consisted of two parts: (1) Accuracy of the different windows of the signal acquisition. (2) Observation of elapsed time and command transfer rate for controlling the simulated power wheelchair.

4.1. Proposed algorithm

4.1.1. Calibrating and parameter setting

Before testing, users performed the actions listed in Table 1. The baseline parameters must be obtained for the threshold parameters \( T_{S(i)} \) in Eq. (10), which are calculated as equation follows:

\[
T_{S(i)} = B_{S(i)} - 0.25B_{S(i)}, \quad (10)
\]

where \( B_{S(i)} \) represents the baseline parameters of the piezoelectric signals obtained from piezoelectric sensors, \( i \) is defined as the index number of sensors (\( i = 1, 2, 3, \ldots, 6 \)), and \( P_{S(i)} \) represents the maximum value of each action calculated according to Eq. (11). Ten values were used to calculate the mean maximum to create six threshold parameters as follows:

\[
B_{S(i)} = \text{mean}(P_{S(i)}(1), P_{S(i)}(2), P_{S(i)}(3), \ldots, P_{S(i)}(10)) \quad (11)
\]

The features acquired during the action movements, \( D_{S(i)} \), are defined as the feature parameters in Eq. (12), which are calculated as follows:

\[
D_{S(i)} = \text{max}(R_{S(i)}[1], R_{S(i)}[2], \ldots, R_{S(i)}[m]), \quad (12)
\]

where \( R_{S(i)} \) are the piezoelectric signals acquired in real-time processing. With the number of samples (\( m \)), we tested a time access evaluation with three numbers, that is, 250, 500, and 1000 for window sizes of 0.25, 0.5, and 1 s, respectively. A sampling rate of 1000 Hz was used, and the real-time features acquired during action \( E_{S(i)} \) in Eq. (13) were calculated as follows:

\[
E_{S(i)} = \begin{cases} (D_{S(i)} - T_{S(i)}) > 0 & \text{if } D_{S(i)} - T_{S(i)} > 0 \\ 0 & \text{if } D_{S(i)} - T_{S(i)} < 0 \end{cases} \quad (13)
\]

As the feature parameters were acquired, argument max was used to detect the activated sensor index in Eq. (14) Output parameter, which was calculated as follows:

\[
\text{Output} = \arg \max_i (E_{S(1)}, E_{S(2)}, E_{S(3)}, \ldots, E_{S(8)}) \quad (14)
\]

4.1.2. Decision making

As the output value was generated, we used a simple decision rule using the Output value for seven command classifications (Table 1) using the index number of sensors (\( i \)) according to the

| Wheelchair Steering | Command Translations | Proposed #1 | Proposed #2 |
|--------------------|----------------------|-------------|-------------|
|                    | Commands | Target Sensors | Commands | Target Sensors |
| Forward (↑)       | 3        | S3            | 3          | S3          |
| Backward (↓)      | 4        | S4            | 4          | S4          |
| Turn Left (←)     | 5        | S5            | 1          | S1          |
| Turn Right (→)    | 6        | S6            | 2          | S2          |
4.2. Proposed command translations

In this work, we proposed the two command translation patterns for simulated wheelchair control by employing facial muscle actions with human cognition. Moreover, we asked the participants about an effortless movement to define a forward and backward command. Most subjects reported pushing the tongue on the upper lip. We proposed other actions for turn left and turn right controls following the left and right sides of the human body. In Table 3, two command translation approaches are implemented and verified. First, we steered the directions of the simulated wheelchair forward, backward, turn left, and turn right by tongue actions (Table 1) to activate the target sensors as S3, S4, S5, and S6, respectively. In the second approach, we used a combination of eye and tongue actions. We used tongue actions to steer it forward and backward via sensors S3 and S4, respectively. Winking the left eye activates sensor S1 to turn it right. The left eye winks to active sensor S2 to turn it right.

4.3. Experimental results and discussions

4.3.1. Experiment I: verification of the proposed commands translations

The same group of participants from the previous experiment participated in this study. All participants had a training session for 15 min on how to operate the HMI system using piezoelectric sensors for simulated wheelchair control. Each subject performed the task following the sequence listed in Table 4, consisting of 12 commands. Before proceeding to the subsequent trial, participants rested for 2 min. Each proposed command translation included three trials for three windows (0.25, 0.5, and 1 s). A total of 108 commands were used per translation of the proposed command. Before proceeding to the second proposed command translation, the participants rested for 5 min to avoid muscle fatigue.

Figure 7 shows that the average classification accuracy of each command translation approach was more than 90%, and the average classification accuracy using the proposed algorithm and command translations with different time processing ranged from 95.0% to 98.3%. The second proposed method achieved the maximum accuracy with a window of 0.5 s. Compared with the first proposed method, with all window sizes of processing, the second method has more than 2% of average accuracy. That may have occurred because the sensor position around the mouth (Figure 4(a)) can generate interference between sensors. For statistically significant between the command translation patterns, the paired t-test (n = 36) indicated that there was a significant difference between the accuracy of the first pattern and the second pattern (p = 0.0066; p < 0.05). Therefore, we employed the second proposed method to control the simulated power wheelchair in Experiment II.

4.3.2. Experiment II: performance of the proposed HMI system for simulated wheelchair control

Real-time steering of the simulated wheelchair in the miWE application [35] was employed to verify the user and proposed HMI system, as shown in Figure 8(a). Before starting, we recorded the time each participant controlled the wheelchair simulator via a joystick (the usual method) as shown in the testing trail in Figure 8(b) for baseline collection for the evaluations. Each participant then performed the proposed HMI system to control the wheelchair simulator freely following the testing trial three times for each command translation pattern. The time spent from start to stop was recorded to evaluate the proposed control modalities and resulting user performance. An example of this experiment is shown in Figure 8(c).

The results of the efficiency comparisons between the proposed command translation patterns and the joystick, with the time spent steering the simulated power wheelchair, are illustrated in Figure 9. The average time spent using the joystick (normal control method) was 24 s. The time required for the first pattern was 57 s. The time required for the second pattern was 45 s. The difference in average time spent between the first command translation and joystick was 33 s, whereas the average time spent on the second command translation and joystick was 21 s. Moreover, the least amount of time spent steering by the first pattern was 31 s and using the second pattern was 30 s, for Participant 1; using joystick control took only 15 s for Participant 6.

Furthermore, we found that the second pattern achieved a higher efficiency than the first command translation. Participants 2 and 3 demonstrated high efficiency when using the second pattern; the efficiency was close to that achieved using joystick control. We found that Participant 8 produced a higher efficiency in the first pattern than that in the second pattern. In addition, we compared the efficiency between the proposed command translation patterns for all participants using double the average time spent using the joystick (as 24 × 2) 48 s. The first pattern had four of 12 participants (33.3%) who spent less than 48 s, while the second pattern had nine of 12 participants (75%). Moreover, the paired t-test was used to test a statistically significant difference between the first and second command translation patterns. The paired t-test (n = 36) indicated that there was a significant difference between the accuracy of the first pattern and the second pattern (p = 0.0033; p < 0.05). Efficiency benchmarking with a previous study, using a facial EMG signals-based HMI for real-time control [14], showed that the proposed system could produce an elapsed time and command transfer rate similar to those of previous studies. According to these results, thin-film piezoelectric sensors can detect facial movements during facial and tongue movements. Compared to conventional EMG electrodes, piezoelectric sensors do not require an electrolyte solution that can reduce signal changes over a long period. However, concerning sensor installation, the wire can produce a disadvantage. A wearable signal-acquisition device with a wireless module could be developed in the future. Besides, time and frequency domain features with the MI classifications model will be

| Sequence No. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|--------------|---|---|---|---|---|---|---|---|---|----|----|----|
| Steering     | → | ↑ | ↓ | ← | ↑ | ← | → | ← | → | ←  | ←  | ↑  |
verified. Furthermore, user performance needs to observe for practical use in actual patients.

In addition, the proposed HMI system can be further implemented in a real power wheelchair for quadriplegic patients who retain control in the face or tongue muscles. The contributions of this study are as follows: (1) it takes less time to train. (2) We observed that fatigue was slow, especially when creating continuous commands using tongue movements. (3) The proposed system can produce a control performance that is quite close to that of the joystick control. (4) The six control commands can be used to control both the speed and direction of the electric wheelchair. Tongue movement can produce a level signal. (5) The signal-acquisition device can be developed into wearable and wireless devices.

Figure 8. (a) Graphic user interface (GUI) for simulated wheelchair control. (b) Sample of the experimental setup. (c) Testing trail with a distance of 20 m.

Figure 9. Average times taken by all participants to complete the trail.
for several applications. (6) The proposed system can be used to control various types of assistive devices, such as electrical and assistive communication devices, or in combination with intelligent systems or machines.

5. Conclusions

In this study, we demonstrated the use of piezoelectric sensors to measure muscle actions in an HMI system-controlled wheelchair. According to the observation features and classification methods in offline testing, thin-film piezoelectric sensors with the proposed positions can detect facial muscles during winking and tongue movements. Six commands and one neutral command channel were generated for wheelchair steering. The MAX feature with KNN and LDA classifiers for offline testing produced high classification accuracy. For online testing, we used the MAX feature and the proposed simple classification algorithm to detect facial muscle actions from sensors to translate them into commands for wheelchair direction control. The two patterns of command translation were evaluated using simulated wheelchair control. The results showed that integrating tongue actions and winking yielded high efficiency similar to joystick control. We aim to implement the proposed HMI system to incorporate an intelligent wheelchair for quadriplegic patients. A comfortable signal-acquisition device that employs wearable tools; Wrote the paper. Yoon Punsawad: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed tools; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interest's statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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