SUMMARY In this paper, a Happiness Cups (H-cups) system is proposed to bi-directionally convey the holding-cup motions of paired cups between two remote users. To achieve this goal, the H-cups system uses three important components. Firstly, paired cups are embedded with accelerometers and gyro sensors to transmit the three-dimensional acceleration and angular signals to a motion recognizer application. This application is designed on an Android phone. The sensors then receive the remotely recognized motions and flash a specific color on the local cup’s RGB-LED via Bluetooth. Secondly, the application considers holding-cup motion recognition from the cup based on long short-term memory (LSTM) and sends the local recognized motion through an intermediate server to transmit to the remote paired cup via the internet. Finally, an intermediate server is established and used to exchange and forward the recognized holding-cup motions between two paired cups, in which five holding-cup motions, including drinking, horizontal shaking, vertical shaking, swaying and raising toasts are proposed and recognized by LSTM. The experimental results indicate that the recognition accuracy of the holding-cup motion can reach 97.3% when using our method. 

key words: motion recognition, internet of things, long short term memory, health care

1. Introduction

During the past decade, many scholars have investigated well-being [1]–[3] and health care [4]–[6]. In [7], the authors indicated that mental health was associated with autonomy, environmental mastery, personal growth, positive relationship with others, and life goals. In [8], it was indicated that one of the important sources of personal well-being is harmony among interpersonal relationships. Mobile phones are one among the technological advances by which people communicate with each other; smart cities with advanced transportation systems that reduce the time needed to visit friends and the internet, which allows people to contact each other and locate them using communication software on their smartphone or computers, are other examples of such technological advances. The development of technology has shortened the distance among people. In [9], it was illustrated that social media was a part of the “social glue” that helped students settle into university life. While rapid technological development has simplified human life, it has also caused alienation among people [10]. People are too dependent on technological products and spend most of their time using computers, tablets, and smartphones. They use technology to communicate with people all over the world, but their actual interpersonal interactions are low. Humanity is becoming more indifferent to people. In [11], it was indicated that technological products themselves did not cause alienation between people. Instead, “loneliness” made people rely on technology. Our goal is to eliminate loneliness and increase social interactions. A new interdisciplinary research area, Orange Technology [12], which involves the integration and innovation of health, happiness, and care technologies, has recently come to the fore. The vision of Orange Technology is to advance health, happiness, and humanistic care among human beings [13]. This work is inspired by Lover’s Cups [14], which add more emotional channels, thereby improving the quality of personal interconnections. The reason for choosing the cup in this study is because it is commonly used in daily life. Further, drinking water is important for health [15], [16]. In [17], it is noted that drinking two to three liters of water a day is beneficial. Therefore, we have designed a drinking water reminder mechanism by which users can set reminders through an application. This mechanism also allows people in different places to interact with each other remotely by drinking and raising toasts with a cup. Therefore, we have enhanced the idea of Lover’s Cups by enabling the mechanism to recognize holding-cup motions, such as drinking, shaking, swaying, and raising toasts, using only an accelerometer. Accelerometers are being increasingly embedded in many electronic devices such as smartphones, remote controllers, or vehicles [18]–[20]. Moreover, holding-cup motion recognition can be regarded as a kind of gesture recognition. The field of gesture recognition with inertial sensors has been extensively explored in the past [21], [22]. Hsu et al. [23] utilized an accelerometer, gyroscope, and magnetometer for handwriting and gesture recognition. Amma et al. [24] demonstrated a hands-free mobile text input device with an accelerometer and a gyroscope. In addition, several studies have investigated gesture recognition with only an accelerometer [25], [26]. As far as gesture recognition methods are concerned, the hidden Markov models (HMM) have been utilized to recognize continuous handwriting words [24]. Other methods such as dynamic time warping (DTW) have been employed to identify isolated handwriting numerals, English lowercase letters, and hand
gestures [23].

Long short-term memory (LSTM) is implemented in this study. LSTM is a recurrent neural network architecture that was proposed in [30]. LSTM was originally developed to address gradient decay or gradient blow-up problems. Technology is always inspired by human nature. The goal of this study is to apply the concepts of health, happiness, and the offering/caring/warming (OCW) model to improve wellbeing, happiness, and health care in our daily life. In this study, the design and implementation of a Happiness Cups (H-cups) system for communication using cups as well as holding-cup motion recognition methods based on LSTM are proposed. Therefore, the system is composed of the hardware and firmware design of the cup, a server for pairing two distant cups, and an Android application that not only acts as a medium between the cup and server but also executes the holding-cup motion recognition.

The remainder of this paper is organized as follows: In Sect. 2, the system design and implementation of the proposed holding-cup motion recognition methods are introduced. In Sect. 3, we introduce our proposed approach. In Sect. 4, experimental results are presented and discussed to validate the proposed approaches. Finally, Sect. 5 presents the conclusions and describes important future research directions.

2. Proposed System Architecture and Design

This section introduces the architecture of the H-cups and the entire H-cups system. Figure 1 shows the overview of the H-cups system. Two H-cups are paired, and two distant cups are connected through the internet. However, most networks (i.e., Wi-Fi) use network address translation (NAT), which allows outbound connections (from the device to the internet) but prevents inbound connections (from the internet to the device). Therefore, the two distant cups cannot directly connect and require a server (that we named “MalteseAnn”) to pair with each other. However, the H-cups only has a Bluetooth wireless interface; therefore, an Android application was designed, so that an Android phone could serve as an intermediary between the cup and server. Moreover, the Android application also analyzed the acceleration signals from the H-cups and identified the holding-cup motion. The recognizable holding-cup motions include drinking water, toasting, swaying, horizontal shaking, and vertical shaking. In this study, LSTM-based methods for motion recognition are proposed. Details of this methodology and comparisons with other methods are provided in the following sections.

The summary data flow between two cups is depicted in Fig.1 and described as follows: The H-cups collects acceleration signals and transmits a batch of signals to the Android phone through Bluetooth. The application in the Android phone analyzes the acceleration signals and transmits the identified holding-cup motion to the server (MalteseAnn). The server (MalteseAnn) passes the identified holding-cup motion to the paired one. Finally, the distant H-cups receives the identified holding-cup motion and generates the corresponding response using an RGB-LED. The LED control task is responsible for showing the holding-cup motion of the distant cup using an RGB-LED.

2.1 Happiness Cups

The H-cups is composed of four major components: a microcontroller (PIC32MX270F256D), a three-axis accelerometer and gyro sensor (MPU6050), a Bluetooth module (BTM805CL2B), and an RGB-LED; the prototype of this system is shown in Fig. 2. The accelerometer is used to acquire acceleration signals generated by holding-cup movements. The microcontroller collects the acceleration signals and transmits a batch of signals to other devices via the Bluetooth module; moreover, it can receive messages from other devices through the Bluetooth module and show the corresponding response on the RGB-LED. The system stack of the microcontroller (PIC32MX270F256D) can run three tasks concurrently on FreeRTOS. The sensor data processing task collects raw acceleration data from the accelerometer; the data are retrieved at 100 Hz. The Bluetooth communicating task drives the Bluetooth module, and transmits 25 sample points simultaneously to the Android phone. Moreover, the Bluetooth communicating task also parses received messages, such as the holding-cup motion of the distant cup and control commands. The LED control task is responsible for showing the holding-cup motion of the distant cup via an RGB-LED. The corresponding colors of each motion are shown in Table 1.

![Fig. 2 System stack of H-cups.](image)

| Holding-Cup Motion | RGB-LED Color |
|--------------------|---------------|
| Drinking           | Yellow        |
| Raising toasts     | Purple        |
| Horizontal shaking | Green         |
| Vertical shaking   | Red           |
| Swaying            | Aquamarine    |

![Fig. 1 Schematic of the entire H-cups system.](image)
2.2 Android Application for Connection between Cup and Server

As described above, the Android phone application acts as an intermediary between the cup and server. Moreover, the application also analyzes the raw acceleration data and performs motion recognition. The flow chart of the application is depicted in Fig. 3, and details are provided in subsequent paragraphs.

2.2.1 Communication

There are two threads responsible for Bluetooth and Internet (Wi-Fi or cellular networks) interactions. The Bluetooth service thread is responsible for interaction between the Android application and the H-cup. Thus, it receives the raw acceleration data stream from the H-cups and passes it to the motion recognition thread to analyze the signals and transmits the motion of the distant cup to the H-cup. The Internet service thread is responsible for interaction with the server (MalteseAnn). Therefore, it transmits the recognition result to the server for the distant H-cup and also receives the motion of the distant cup from the server. The received message is passed to the Bluetooth service thread.

2.2.2 Holding-Cup Motion Recognition

The motion recognition thread is responsible for parsing the raw data stream received by the Bluetooth service thread. Next, the motion recognition thread commences the testing phase. The recognition result is passed to the Internet service thread for the distant H-cup. In this study, an LSTM-based motion recognition method has been implemented. The details are described in Sect. 3.

2.3 Server for Pairing Distant Cups

As mentioned above, the two distant cups require a server for pairing. As the Android phone only knows the private IP address, the connection between two devices cannot be established directly. Therefore, as depicted in Fig. 4, the server records the public IP address of each device and matches devices with the same pairing IDs. Once two distant cups are paired by the server, the data transfer between cups can be regarded as a direct connection. As the server knows the public IP address of the paired cups, it can pass the received message from one cup to another.

Figure 5 illustrates the message transfer between the cup and server. Two cups are paired together by providing the same pairing ID. While a cup (client) is connected to the server, the server will allocate a thread to serve it. The threads with the same pairing IDs are able to communicate through queues (interthread communication). A working thread is illustrated in Fig. 6.

3. Proposed Approach

In this section, we describe the calculation process for the
H-cups system. The schematic of the proposed H-cups system is presented in Fig. 7. The input signals are acquired from the built-in accelerometer and gyroscope sensors of the H-cups system. The signals captured from the accelerometer and gyroscope sensors provide triaxial linear acceleration and angular velocity information respectively. Subsequently, the combined feature vector is fed to the classifier to determine the activity performed by the user. It performs direct end-to-end mapping from raw sensor data inputs to activity label classifications. It classifies the label of an activity performed during a specific time window. The input is a discrete sequence of equally spaced samples, where each data point is a vector of individual samples observed by the sensors at time. These samples are segmented into windows with a maximum time index $T$ and fed to an LSTM model. A fully connected layer that follows LSTM layers is used for producing an output prediction. A softmax layer and then a classification layer follow the final fully connected layer. The model output recognizes actions such as toasting, horizontal shaking, vertical shaking, drinking and swaying.

3.1 Data Acquisition

The dataset contains five activities: 0-horizontal shaking, 1-vertical shaking, 2-swaying, 3-raising toasts, and 4-drinking. We collected data from 10 volunteers, with approximately 15000 labeled activities as training and test data. The test set was separated entirely from the training dataset during our experiments. Further, to avoid overfitting the model with training data, 20% of the training dataset was held back as a validation set. The set of input signals consists of linear acceleration and angular velocity signals collected using the built-in accelerometer and gyroscope sensors of the H-cups system while the user performs different activities. The triaxial linear acceleration and triaxial angular velocity signals are denoted as $a_x$, $a_y$, $a_z$, and $g_x$, $g_y$, and $g_z$, respectively. Figures 8–12 show typical patterns of sample accelerometer sensor signals along the $x$, $y$ and $z$ di-
rections for different activities. Patterns corresponding to most of the activities are distinct. For example, acceleration signals along the $x$ and $z$ directions show distinct patterns for horizontal shaking and swaying. As features play a significant role in the classification of activities, a careful observation of the signals indicates that the feature descriptors need to be designed to effectively characterize patterns of evolution of these signals.

The overlapped sliding window method [27] is applied, which segments data into many short data. It accumulates sensor data over a fixed time window that shares common data samples between time intervals. Depending on the percentage overlap, more or less data overlaps from window $N$ into $N + 1$ referred to as a window shift. A 0% overlap corresponds to the overlapping slide window segmentation method, while an overlap of 100% would yield a static window that would not shift, and the data would always be segmented at the exact same point. Therefore, the requirement for the overlapping sliding window is to move with at least one data point per segmentation. The length of interval and the number of segmentation windows generated can be calculated using the following equations:

$$\text{Length}_{\text{Interval}} = \frac{\text{Rate}_{\text{Sampling}} \times \text{WindowSize}}{S}$$

$$\text{Segmentation}_{\text{windows}} = \frac{S}{L_i - L_i \times P_j}$$

where $S$ is the total number of signal samples, $\text{Rate}_{\text{Sampling}}$ is the data resampling rate used, $\text{WindowSize}$ is the selected window size. $P_j$ is one of the following percentage overlap values used in this research: 25%, 50%, or 75%.

3.2 Long Short-Term Memory Network

In this paper, we propose a posture recognition system for H-cups based on the holding H-cups patterns of individuals. We consider the data from the sensors on the cups to ease the computational burden. We further implement the enrollment and recognition phases on the cloud, leaving only the capture module on the device. In our approach, the feature extraction process is based on a deep-learning LSTM, which achieves a competitive accuracy result. A recurrent neural network is one that attempts to model time or sequence-dependent behavior, such as language, stock prices and electricity demand. These are "unrolled" programmatically during training and prediction, as shown in Fig. 14. An LSTM network is a recurrent neural network with LSTM cell locks in place of the standard neural network layers. These cells have various components, namely, the input gate, forget gate, and output gate. The main component of the LSTM layer is a unit called a memory block. An LSTM cell state is the key component which carries information between each LSTM block. Modifications to the cell state are controlled with the three gates described above. An LSTM single cell, as well as the manner in which each gate is connected and the cell state itself, are shown in Fig. 15.

The key component of the LSTM unit is the cell which has a state $C_t$ over time. The LSTM unit decides to modify and add the memory in the cell via the sigmoid gates input gate, forget gate and output gate. These updates for the LSTM unit are summarized as follows: first, the LSTM cell decides on how important the previous state in the cell
3.3 Softmax Classifier

The output for the hidden state of the final cell in the second LSTM network is the input to a fully connected layer, which uses a basic neural network with one hidden layer to train the output data using the softmax classifier. A simple softmax classifier is used to recognize activities at the last layer. The softmax function is widely adopted due to its simplicity and probabilistic interpretation [28], [29]. The final result is a probability value, which informs us of the probability that the data will be considered as an activity. The probability is defined by Eq. (9).

\[
P = \arg \max_c p(y = c|x) = \arg \max_c \frac{\exp(o_t)}{\sum_{k=1}^K o_t}
\]

where \( c \) is a class label, \( x \) is a sample feature, \( y \) is the label variable and \( K \) is the number of classes. This decision is made by considering the previous state \( h_{t-1} \) and the current input \( X_t \).

3.4 Training

In order to obtain a better neural network model, regularization and hyper-parameters are considered. When there are large weights, regularization can add an extra term into the cost function which penalizes the large weights. In this work, L2 regularization was adopted, and is defined in Eq. (10).

\[
E = E_0 + \lambda \sum_w W^2
\]

where \( E_0 \) is the original cost function, \( \lambda \) is the weight decay coefficient, and \( W^2 \) is the penalization term.

We trained the parameters in the LSTM using backpropagation. We also used the Adam optimizer for improving the efficiency of optimization [30]. Adam is an adaptive learning rate optimization algorithm that’s been designed specifically for training deep neural networks and computes individual learning rates for different parameters.

4. Experimental Results

In this section, we evaluate the LSTM in the H-cups system. We first introduce our experimental settings, including the hardware, dataset, parameters setting and baseline algorithm. We then evaluate our design in terms of accuracy and energy consumption. Experimental comparisons are provided for the recognition results from machine learning and the LSTM-based methods.

4.1 Experimental Environment

We conduct experiments with a personal computer as the server, where the CPU is Intel(R) Core (TM) i9-9700k CPU @ 3.60 GHz and the graphics card is NVIDIA GEFORCE
GTX 1080 Ti. We set up a deep learning programming environment Python3.6 [31], TensorFlow [32] and CUDA8 [33] under the Ubuntu operating system to construct LSTM. Thereby, we realize the deep learning framework with Python directly.

4.2 Dataset Collection

In this section, the H-cups system associated with holding-cup motion recognition methods was validated. For this, 10 subjects (5 females and 5 males) volunteered to record activities. The volunteers were in the age range of 20 to 35 years, and weighed between 55 kg and 85 kg. In all, five actions were recorded in this experiment. Each subject repeated the same action for approximately 60 s on average. The interval between each action was 1 s. Thus, we obtained 15000 samples for each activity on average. The raw signals contain information about the 3D angular velocity, 3D orientation (roll, pitch, and yaw), and 3D user acceleration when the sampling frequency is 50 Hz. In the dataset, 15000 holding-cup motion sequences were collected from the ten subjects in a laboratory environment, in order to train and perform validation. The number of samples per action category is 3000.

The overlapped sliding window method [27] is applied, which segments data into many short data. The percentage overlap values used in this research: 25%, 50%, or 75%. After experimental comparison, the length of each window is set to 1 second, while the degree of overlapping is set as 50%, which has a higher accuracy as shown in Fig. 16.

4.3 Parameter Setting

We conducted an experiment to decide the number of iterations. We used the Adam optimization algorithm to minimize the cost function by backpropagating its gradient and updating the model parameters. The dropout technique was used to avoid overfitting in our model. Although dropout is typically applied to all nodes in a network, we followed the convention of applying dropout to the connections between layers. The probability of dropping a node during a training iteration is determined by the dropout probability, which is a hyperparameter tuned during training and represents the percentage of units to drop. Adopting the dropout regularization technique led to a significant improvement in performance by preventing overfitting. In the accuracy and cost of training and testing processes, the gap between training and testing accuracies, as well as the gap between training and testing costs, is very small. This indicates that the dropout technique were very effective at forcing the model to generalize and be resilient to overfitting, as shown in Fig. 17. Various combinations of parameters such as number of epochs, batch size, window size, learning rate were tried and tested using hit and trial method for hyperparameters tuning. The experimental setup is summarized in Table 2.

4.4 Comparison Methods

We considered the following comparison methods:

- Support vector machine (SVM) [34]: SVM represents the problem as a frequency-weighted vector of significant terms and classifies by vector partitioning. The value of parameter \( \log_2 C \) was obtained in the range from \(-5\) to \(15\), with an interval of \(2\), and \(\log_2 \gamma\) in the range from \(-15\) to \(3\), with an interval of \(2\) by using cross validation and grid search. The parameters are kernel: rbf, \(C\): 8 and \(\gamma\): 0.5.
- K-nearest neighbor (KNN) [35]: The KNN classifier is a supervised learning algorithm that makes predictions without any model training by choosing the k nearest neighbors for classification and a distance metric. The number of neighbors is 5.
- Random forest classifier (RFC) [36]: RFC is a meta estimator that fits a number of decision tree classifiers on
various subsamples of the dataset. The best parameters are number of estimators: 1000 and max depth: 9.

- Artificial neuron network (ANN) [37]: ANN is a computational model based on the structure and functions of biological neural networks. (Dense: 40, input dim: 6, kernel initializer: uniform, activation: ReLU, and activation: softmax.)

4.5 Evaluation Settings

To evaluate the system performance, standard measurements were used. The corresponding equations are as follows:

- Accuracy: Measures the proportion of correctly predicted labels over all predictions.

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}
\]

- Precision: Measures the number of true samples out of those classified as positive. The overall precision is the average of the precisions for each class.

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{12}
\]

- Recall: Measures the number of correctly classified samples out of the total samples of a class. The overall recall is the average of the recalls for each class.

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{13}
\]

- F1-score: A harmonic mean of precision and recall.

\[
F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{14}
\]

where \( TP \) is the overall true positive rate for a classifier on all classes, \( TN \) is the overall true negative rate, \( FP \) is the overall false positive rate, and \( FN \) is the overall false negative rate.

4.6 Experimental Results for Motion Recognition Methods

Comparison of the different holding-cup motion recognition methods is provided in Table 3. The cross-validation [38] is applied in the training phase to tune the recognition methods. In accuracy, the ANN method achieves 82%, the KNN method achieves 92%, the SVM method achieves 87% and the RFC achieves 81%. The proposed method achieves 97%. In precision, the performance of the other algorithms range from 82% to 93% while that of our proposed method is 97%. In recall, the other algorithms exhibit performance in the range of 82% to 93%, while our proposed method exhibits 97% performance. In terms of the F1-score, the performance of other algorithms range from 81% to 93% while that of our proposed method is 97%. In the outside and inside tests, the proposed method improves the recognition accuracy more than others. In general LSTM models outperform others in the experiment, because LSTM is good at handling the time series [39], [40]. It maintains the relation of the input sequence, which other models do not. It is a type of recurrent neural network that can learn the order dependence between items in a sequence. Therefore, LSTM can learn the context required to make predictions in time series forecasting problems. Hence, the LSTM-based holding-cup motion recognition method is more fault tolerant and efficient.

4.7 Matrix Confusion Report of Experimental Results

We use the confusion matrix as the representation accuracy evaluation. Tables 4–8 show the confusion matrix reports on the LSTM model and comparison methods with the testing data. In the matrix report on LSTM model, the values of prediction in the five classes are in the range of 93% to 100%, and the values of recall are in the range of 95% to 100%. The integral accuracy reaches 97%. It can be observed that LSTM has good performance in the evaluation of the confusion matrix. Intuitive confusion matrices are shown in Figs. 19 and 20. Each column of the confusion matrix represents the prediction category. Each row represents the true attribution category of the data. The colors from white to blue represent the increasing percentage. It can be seen that the SWAY class is recognized best, likely because the triaxial acceleration and triaxial angular veloc-
Table 4  Matrix report on ANN.

|                         | Precision | Recall | F1-score | Support |
|-------------------------|-----------|--------|----------|---------|
| Horizontal shaking      | 0.70      | 0.68   | 0.69     | 139     |
| Vertical shaking        | 0.98      | 1.00   | 0.99     | 167     |
| Swaying                 | 0.95      | 0.86   | 0.90     | 153     |
| Raising toasts          | 0.64      | 0.55   | 0.59     | 149     |
| Drinking                | 0.79      | 0.99   | 0.88     | 139     |
| avg/total               | 0.82      | 0.82   | 0.81     | 747     |

Table 5  Matrix report on KNN.

|                         | Precision | Recall | F1-score | Support |
|-------------------------|-----------|--------|----------|---------|
| Horizontal shaking      | 0.83      | 0.92   | 0.87     | 139     |
| Vertical shaking        | 0.98      | 1.00   | 0.99     | 167     |
| Swaying                 | 1.00      | 0.95   | 0.97     | 153     |
| Raising toasts          | 0.88      | 0.79   | 0.83     | 149     |
| Drinking                | 0.94      | 0.98   | 0.96     | 139     |
| avg/total               | 0.93      | 0.93   | 0.93     | 747     |

Table 6  Matrix report on SVM.

|                         | Precision | Recall | F1-score | Support |
|-------------------------|-----------|--------|----------|---------|
| Horizontal shaking      | 0.72      | 0.70   | 0.71     | 139     |
| Vertical shaking        | 0.99      | 1.00   | 1.00     | 167     |
| Swaying                 | 1.00      | 0.96   | 0.98     | 153     |
| Raising toasts          | 0.69      | 0.72   | 0.70     | 149     |
| Drinking                | 0.95      | 0.97   | 0.96     | 139     |
| avg/total               | 0.88      | 0.87   | 0.87     | 747     |

Table 7  Matrix report on RFC.

|                         | Precision | Recall | F1-score | Support |
|-------------------------|-----------|--------|----------|---------|
| Horizontal shaking      | 0.57      | 0.69   | 0.63     | 128     |
| Vertical shaking        | 0.99      | 1.00   | 1.00     | 173     |
| Swaying                 | 0.99      | 0.88   | 0.93     | 153     |
| Raising toasts          | 0.62      | 0.48   | 0.54     | 149     |
| Drinking                | 0.87      | 1.00   | 0.93     | 139     |
| avg/total               | 0.82      | 0.82   | 0.81     | 747     |

Table 8  Matrix report on LSTM.

|                         | Precision | Recall | F1-score | Support |
|-------------------------|-----------|--------|----------|---------|
| Horizontal shaking      | 1.00      | 0.96   | 0.98     | 139     |
| Vertical shaking        | 0.95      | 0.96   | 0.96     | 167     |
| Swaying                 | 1.00      | 0.99   | 1.00     | 153     |
| Raising toasts          | 0.93      | 0.95   | 0.94     | 149     |
| Drinking                | 1.00      | 1.00   | 1.00     | 139     |
| avg/total               | 0.97      | 0.97   | 0.97     | 747     |

4.8 Power Consumption

The power consumption of each major component is listed in Table 9. PIC32MX270F256D (chip) consumes 108.78 mW/s and MPU-6050 (sensor) consumes 14.06 mW/s. The power consumption under different transmitting periods is shown in Fig. 21. The battery life under different sensor data transmitting periods is summarized in Fig. 22. When the sensor data transmitted in periods of 2 seconds, the corresponding power consumption was 307.84 mW (83.2 mA at 3.7 V), enabling approximately 24 hours of operation time with a 2000 mAh Li-ion battery, which is appropriate for daily-use scenarios. When the data transmitting period extends to 1 minute, the battery life is approximately 56 hours. This shows that when the rate of transmission increases, it will increase the speed of power consumption.
Figure 21: Power consumption for different data transmitting periods.

Figure 22: Battery life for different data transmitting periods.

Figure 23: Experimental results using questionnaire.

4.9 Questionnaire Result

We report on two scales from the brief questionnaire that was provided to the volunteers following each interaction session. We use the Likert scale questionnaire to investigate the responses [41]; the Likert Scale is a rating scale typically used when surveying customers regarding their experience for a service provided and the overall effectiveness of the product. The volunteers were asked to indicate their level of recognition of the topic, or any form of subjective or objective evaluation. However, we note that there was a tendency for users to prefer conditions where the H-cups was turned on and interacting with them. Figure 23 shows the users’ responses to the two main scales: a scale to measure the extent of social interaction and a scale of play behaviors that measured how much the users wanted to use H-cups and whether they wanted to continue to do so in the future. The improvement of presence was especially noted, so that the improvement of happiness had a good effect.

5. Conclusions

Herein, we presented a complex system for recognizing the motions of two holding-cups. The system used signals from an accelerometer and a gyroscope as the input, an Android application that applied the holding-cup motion recognition method, and a remote server that paired the two distant cups. Further, the Android application not only acted as a medium between the cup and server but also executed the holding-cup motion recognition method. The proposed holding-cup motion recognition method can identify isolated motions. From the experimental results, the proposed accuracy of the method was 97%. Results of a questionnaire indicated that the volunteers were highly willing to use the H-cup in their daily lives. In the future, we intend to further develop the holding-cup motion recognition method such that it can recognize continuous motions. We also intend to apply a powerful microcontroller/microprocessor instead of a Bluetooth transmitter and Android application to achieve this improvement.

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