RESEARCH ARTICLE

3D Monitoring of Toothbrushing Regions and Force Using Multimodal Sensors and Unity

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ABSTRACT The goal of this study is to help people to monitor brushing process to maintain their oral quality by providing real-time feedback. In this research, a low-cost toothbrushing monitoring system of brushing regions and brushing force using multimodal sensors and Unity is proposed for toothbrushing quality monitoring. An inertial sensor attached to the handle of a toothbrush and Random Forester Classifier (RFC) model were used to estimate brushing regions; five force sensors clipped on the toothbrush and Random Forest Regression (RFR) model were used to estimate brushing force; a visual interface based on Unity was designed to display detection results in real-time. For brushing region detection, the results show that offline verification accuracy is 97.6%, and average accuracy of online detection method is 74.0%. For brushing force detection, 5 subjects were invited to participate in experiment on both User Dependent (UD) and User Independent (UI). The results show that average Root Mean Squared Error (RMSE) is 22.08g for UD experiment; average RMSE is 37.06g for UI experiment. For this 3D brushing monitoring system, 20 subjects were invited to participate in usability experiment. The results show that 3D brushing monitoring system of this research has good usability, performance, and user satisfaction.

INDEX TERMS 3D brushing monitoring system, multimodal sensors, machine learning, random forest algorithm, unity.

I. INTRODUCTION

A. BACKGROUND

Brushing teeth can effectively control the reproduction of bacteria and remove bacterial plaque, which is a very important way to maintain oral health. Brushing twice a day with a fluoride toothpaste can help to keep teeth and gums healthy and avoid the need for costly and time-consuming dental procedures. In recent years, a variety of oral care products have been developed because it is crucial to maintain dental health which affects the overall health of the body directly or indirectly [1]. A report shows that 26% of adults have tooth decay problems in the United States. Another report suggests that 46% of people in the United States show symptoms of gum diseases [2].

In addition, according to the CBNData report, the prevalence of oral cavity in China is relatively high, with 300 million visits in 2018. One of the main reasons for dental problems is that the food residues and the dental plaques often accumulate around the teeth, where various bacteria in the oral cavity multiply, leading to gingivitis and gum bleeding. In addition, a report shows that oral conditions remain a significant population health challenge. Globally, there are 3.5 billion cases of oral conditions, of which 2.3 billion have untreated caries in permanent teeth, 796 million have severe periodontitis, 532 million have untreated caries in deciduous teeth, 267 million had total tooth loss, and 139 million had other oral conditions in 2017 [3]. Besides, 92% of adults between 20 and 64 years had experienced dental caries [4].

This high number does not only lead to the conclusion that many adults have oral health issues, which leads to bad consequences such as pain or dental implants as well as social problems due to loss of teeth [5]. Research has indicated that if plaque is completely removed every other day, there will be no deleterious effects in the oral cavity. On the other hand, because few individuals completely remove plaque, daily brushing is still extremely important for periodontal disease control measure [6].

The proper way of brushing can remove dental plaque, soft dirt, and food residues to maintain oral hygiene and the health of teeth and periodontal tissues. Therefore, it is indispensable for keeping dental health to come up with a method that is able to guides people to learn how to brush their teeth correctly and effectively. In this regard, many dental associations worldwide recommend the Bass Brushing Technique to brush teeth. It's not only easy to learn, but also a scientific way of brushing as it removes plaque efficiently and provides stimulation to the gums. The toothbrush bristles are placed at gum line and are tilted at an angle of 45 degree. They are then moved in a circular action. The circular movement should be small, covering 3 teeth at a time. Each set of 3 teeth should be brushed about 15–20 times. The American Dental Association recommends brushing teeth twice a day for two minutes using a fluoride toothpaste. Brushing for two minutes has been shown to achieve clinically significant plaque removal [7]. However, time is not the only important factor for proper toothbrushing; another important requirement is that all the regions of the teeth should be brushed efficiently. Thus, it is very significant to detect the efficient brushing regions.

In addition, the force on the teeth when brushing has a significant effect on the level of plaque removal by powered toothbrush (PTB) [8]. Toothbrushing force changes depending upon the kind of the brush used and the locality of brushing as well as upon the stiffness or softness of bristle. It is even more influenced by individual brushing activities, that is habits in brushing [9]. The brushing force affects the effectiveness of brushing teeth. If the brushing force is too small, it will not be enough to remove plaque and tartar; if the brushing force is too strong, it will damage the teeth and gums and easily lead to bleeding gums. Therefore, proper brushing force is very important in the brushing process. There have been many automatic electronic toothbrushes available in the market; however, there are some skeptical standpoints for efficacy and safety of electronic toothbrushes. Moreover, most electric toothbrushes are expensive and many people still use common toothbrushes to brush their teeth manually [10]. Thus, it is very meaningful to propose an efficiently solution not only for electric toothbrushes but also for common toothbrushes.

Therefore, we hope to design a lightweight brushing system to detect the brushing regions and brushing force on the teeth and provide a more intuitive visual interface for display the results.

B. PURPOSE

Good oral hygiene is essential for maintaining healthy teeth and gums. However, for many people, they may not use the right method, or they may not brush for long enough or all regions to remove all the plaque from their teeth. This will lead to poor oral hygiene and an increased risk of tooth decay and gum disease.

Therefore, in this paper, we propose a smart toothbrushing system that can help to improve the effectiveness and efficiency of brushing teeth. On the one hand, the smart toothbrushing system can track the movements using the inertial sensor to detect the brushing regions and using force sensor to detect the brushing force. Users can know not only whether all regions are brushed or not but also whether the brushing force is suitable or not. On the other hand, the real-time feedback provided by the visualization interface can instruct users to take a correct way to brush their teeth. Moreover, it also can make the toothbrushing experience more enjoyable and engaging, which can help to motivate users to brush their teeth regularly and consistently.

C. ISSUES AND SOLUTIONS

There are three issues in this system:

1) HOW TO DEFINE AND DETECT BRUSHING REGIONS?

First of all, for the first issue, each set of 2–3 teeth should be brushed about 15–20 times according to the Bass Brushing Technique and many medical studies divide the teeth of people into 16 regions to detect whether brushing is comprehensive and effective. Most adults have 32 teeth, so these teeth are divided into 16 regions in this research. In addition, a 9-axis sensor is a multi-functional sensor that can simultaneously detect the acceleration, angular velocity and magnetic field strength of an object. Besides, the 9-axis sensor can be used to detect the motion and position information of the object, and accurately locate the object by fusing information from different sensors. Therefore, in this research, a 9-axis inertial sensor is used to collect three dimension Euler angles which are used as features to train the RFC model for brushing regions estimation.

2) HOW TO DETECT BRUSHING FORCE?

For the second issue, there are many sensors on the market that can detect force, such as Force Sensitive Resistor (FSR) sensor, optical fiber pressure sensor, piezoelectric thin-film sensor, strain gauge type pressure transducers, etc. The FSR sensor is cheap enough, portable and flexible to detect the brushing force in this system. The brush force on the teeth mainly comes from the force exerted by the hand on the toothbrush when holding the brush. In this research, it is assumed that five fingers exert force on the toothbrush when brushing and then five force sensors are fixed on the handle of the toothbrush according to the positions of the fingers holding the brush. In this way, brushing force can be estimated from the data collected by the force sensors. Furthermore, the

algorithm of RFR is used to estimate the value of brushing force because RFR has high estimation accuracy and can handle more data features.

3) HOW TO VISUALIZE RESULTS?

Regarding the last issue, the purpose of visual detection results is to provide users with toothbrushing feedback. The significance of brushing teeth feedback is to improve the quality and effect of toothbrushing. Users shall know the brushing time, brushing region and brushing force according to toothbrushing feedback and give users guidance to help them better master brushing skills and correct methods. Unity is a professional game engine that can be used to create virtual environments and render graphics in real time. Thus, Unity can make the visualization of toothbrushing detection results more vivid and can directly operate the virtual environment during the experiment process to observe and analyze the experimental results in real time. In addition, Unity can support a large number of data analysis and visualization tools to improve the visualization of experimental results. Therefore, we use Unity to design the visual interface in this research. In this way, it can help users understand their toothbrushing situation easily and how to improve the quality and effect of toothbrushing through data analysis and comparison.

D. CONTRIBUTIONS

The main contributions of this research are as follows:

(1) Firstly, we propose a lightweight method based on a combination of the inertial sensor and machine learning algorithm to detect brushing regions. We also proposed an indirect method using five force sensors and a RFR to detect brushing force. In this research, We combined these two methods onto a toothbrush to detect the brushing region and brushing force at the same time. Therefore, this toothbrush can provide more comprehensive information about the brushing habits of the user, allowing for improving and keeping oral health.

(2) Regarding the visualization interface, we used Unity to design a 3D tooth model to provide rich visualization effects. Therefore, the experimental results displayed by Unity can not only make the experimental results more vivid but also better attract the attention and interest of users. It also allows users to get more intuitive brushing feedback so that it is easier for users to learn how to improve the quality and effect of toothbrushing to maintain good oral health.

(3) In terms of practical application, the multi-functional toothbrushing system designed in this study exhibits a lower cost compared to other expensive electric toothbrushes available in the market. In this study, we designed a low-cost multifunctional toothbrushing system. We used some cheaper sensors, which not only can realize the function of detecting the brushing regions and brushing force, but also save the cost to a large

extent. For example, we have used an inertial sensor to detect the brushing regions and the FSR sensors to detect the brushing force. These sensors are less expensive and can contribute to cost reduction of the system. In addition, we also use some other technical methods, such as machine learning algorithms and data analysis methods, to improve the performance and accuracy of this system, so as to provide users with better brushing guidance and feedback.

II. RELATED RESEARCH

In recent years of research, there are some other techniques for monitoring brushing health or brushing activity. For example, paper [11] used a smart toothbrush with quantitative light-induced fluorescence technology to monitor effectiveness of oral health. Paper [12] proposed a method to estimate the recovery index for fatigue based on halitosis collecting by a smart toothbrush with a halitosis sensor while people are brushing their teeth. Paper [13] designed a computer-assisted toothbrushing system using a toothbrushing instruction (TBI) method called the smart toothbrush and smart mirror (STM) system to instruct users to brush their teeth more effectively. Paper [14] discusses the benefits of smart toothbrushes. The smart toothbrush uses AI technology to improve the brushing experience and oral hygiene outcomes. For region detection, Research [15] proposed a method to infer tooth surface coverage using IMU motion sensors attached to the toothbrush handle and embedded in smartwatches and using Transformer Encoder model to estimate the brushing regions. For visualization, this paper [16] has studied the usability of the smart toothbrush APP user interface. It takes the smart toothbrush APP user interface as the research object and uses a combination of questionnaire research and experimentation to optimize the function of the visual interface. These researches monitor dental health using a single metric, such as brushing region, brushing force, and the impact of visual interfaces. In contrast, our study proposes a novel and comprehensive system that can simultaneously detect brushing regions and force, and display the results through an intuitive visual interface. Therefore, our proposed system is a comprehensive and innovative approach. We also elaborated and compared existing techniques and methods from four aspects: brushing regions detection, brushing force detection, the application of machine learning in toothbrushing system, and the visualization of toothbrushing feedback.

A. BRUSHING REGION DETECTION

In the research [17], a method was proposed to detect the insufficient brushing regions using a six-axis inertial sensor which is clipped onto the handler of a toothbrush. The brushed regions will be displayed on the visual interface after brushing the teeth. All teeth are divided into 16 regions to evaluate the detection accuracy. The user-dependent accuracy is 88%, and user independent accuracy is 72% across five users. However, this method uses on a six-axis sensor

to obtain the vertical angle and horizontal angle and artificially limits the angle range corresponding to each region to detect the brushing regions. There is no machine learning method and it is an offline detection method instead of real-time detection. In the study [18], the authors proposed an advanced smart toothbrush system and a brushing region classification algorithm. The system is based on a three-axis accelerometer, a magnetic sensor, and the tilt compensation azimuth (heading) algorithm, which can reliably distinguish 15 regions based on the brushing posture and specific heading angle. The teeth are divided into 16 regions, but 15 brushing regions could be classified instead of the entire regions. In the research [19], a method was propose for brushing region detection based on three-axis accelerometer and magnetic sensor with a simple k-mean clustering method. In the study [20], a system is proposed to monitor the brushing quality on all 16 tooth surfaces using a manual toothbrush and an off-the-shelf wrist watch. The toothbrush is modified by attaching small magnets to the handle, so that its orientation and motion can be captured by the magnetic sensor in the wrist watch for toothbrushing gestures identification. This research [21] used a 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer combined with the Random Forest machine learning algorithm. The accuracy of the right-handed model is 99.63% and the accuracy of the left-handed model is 99.71% for detecting the brushing tooth and brushing the surface, but the localization detection average accuracy just is 9.0%. In the study [22], a method was propose for user identification based on toothbrushing information collected by the three-axis accelerometer. 11 features extracted from the information captured by a three-axis accelerometer and use Support Vector Machine (SVM) algorithm for identification. This study uses a three-axis accelerometer and a machine learning algorithm, but it is just for user activity recognition rather than toothbrushing detection.

B. BRUSHING FORCE DETECTION

Proper brushing force is important for effective brushing because too much pressure can damage the teeth and gums, while too little pressure may not effectively remove food debris and plaque from the surface of the teeth. The contact pressure of a manual toothbrush is generally 20–400 g, and the brushing force is 200–1000 g [23]. The study [24] presented a toothbrush with an adaptive load sensor and suggested an applied pressure range of 30 g to 150 g. Another research [25] presented the mechanical design of a force-sensitive toothbrush in which the applied pressure on the bristles was in the range of 50 g to 250 g. In recent years, there are some projects about brushing force detection. The purpose of study [26] is to compare and analyze the brushing force after various brushing techniques through the pressure sensing unit installed in the toothbrush, but this study focuses on the impact of various brushing methods on the brushing force rather than detecting the brushing force. Paper [27] presents

the design of a novel instrument for measuring toothbrushing force applied through the bristle axis using an off-the-shelf hollow-handled toothbrush. Its advantage is that the system is easy to integrate, and the foil strain gauge force sensor is used for experimental stress analysis to measure tensile and compressive forces, but its disadvantage is that there is no evaluation accuracy for the detection force. This study [28] presents the design of a force-sensitive classic toothbrush which will ensure the pressure applied during brushing. The Force Sensitive Resistor (FSR) is placed beneath the bristles to get a feedback of the pressure applied on teeth by the bristles, but the system is very complicated. The study [29] also used this FSR sensor to detect changes of force, but it is just used to differentiate between strong and weak forces.

In research [30], a prototype of a smart toothbrush with force sensors placed underneath the bristles was proposed, which can detect induced pressure on the bristle and alert the user through LEDs. However, this method has very high requirements on the mechanical design of the toothbrush. The toothbrush requires a thin layer to be cut from the back of the brush-head (not separated from the brush-neck) and foam with FSR sensor is placed between the brush-head and the thin-cut layer. Another project [31] detects the brushing force during brushing by placing a force sensor and an acceleration sensor on the toothbrush handle, respectively, and a visual interface is designed to display the detection results. Although the detection error using the force sensor is much smaller than that using the acceleration sensor, the error is still large. The study [32] designed and developed a new oral care simulator to measure and visualize brushing force. An anatomically accurate mandibular jaw and 16 teeth were 3D printed, on which 16 force-sensing structures for detecting the force on teeth were embedded. The main application of this oral care simulator can provide accurate and reliable feedback on the force applied to a nurse brushing a subject's teeth, allowing nurses to practice and improve their techniques. However, it cannot detect the brushing force of the toothbrush against the teeth while brushing.

C. APPLICATION OF MACHINE LEARNING IN TEETH BRUSHING SYSTEM

In another research [17], the filtered accelerometer data and the integrated gyroscope data collected from 3-axis accelerometer and 3-axis gyroscope are used as features to train a Support Vector Machine (SVM) Classifier. The 70% of the samples are used to train the model and 30% are held back for evaluation. However, it is only used for human activity recognition applications but not for brushing regions recognition. Study [33] proposed a Recurrent Probabilistic Neural Network (RPNN) for toothbrush posture recognition and compared with Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) methods. The RPNN model is trained for toothbrush posture recognition and brushing position and then monitors the correctness and integrity of the Bass Brushing Technique.

Study [34] presented a new method for evaluating toothbrushing performance using audio collected from smartphones. Markov models (HMMs) are used to recognize smartphone sound data of toothbrushing, which includes various types of brushing behaviors. Then, the output data from HMMs was used to build a regression model to estimate brushing performance score. In this research [35], various machine learning algorithms are examined, utilizing the data collected by real-time sensors on the toothbrush for the localization of the toothbrush in the mouth of the user. A final dataset of more than one million rows (1.44M), seven features and seventy-two classes is tested with KNN, Naive Bayes, Support Vector Machines, Extra Trees Classifier and various voting classifiers. The results show that the ExtraTrees classifier is the most promising method of the evaluated algorithms compared across various dimensions such as estimation performance, model training, estimation overhead and model size.

D. VISUALIZATION METHOD OF BRUSHING FEEDBACK

Study [36] describes a method for visualizing the effect of toothbrushing technique on plaque removal using 3D printed models and a laser profilometer. In this study, the researchers used 3D printed models to simulate real teeth and a laser profilometer to measure the thickness of plaque. They also used different toothbrushing techniques and measured each technique to determine the effect of the toothbrushing technique on plaque removal. Study [37] discusses the design of an augmented reality toothbrushing technique visualization system. In this study, the researchers designed a toothbrushing visualization system using augmented reality technology. The system uses a smartphone camera to capture images during the toothbrushing process, and displays augmented reality images on the smartphone screen. This visualization system can help users better understand the correct toothbrushing technique, and provide real-time feedback during the process. The researchers conducted a series of experiments and found that the use of the system significantly improved the user's toothbrushing technique compared to those who did not use the system. This study suggests that augmented reality toothbrushing visualization systems can be an effective tool for helping users improve their toothbrushing technique.

E. PREVIOUS WORK

In our previous work, for brushing regions detection, we propose a lightweight method based on a combination of inertial sensor and machine learning algorithm to locate brushing positions. The data collected by the inertial sensor is used to train the RFC model to estimate brushing regions [38]. For brushing force detection, we proposed an indirect method to detect brushing force. The five force sensors were fixed on a toothbrush to simulate the brushing action on an electronic balance. Data obtained by the force sensors were used as features and data collected from electronic balance was used as label for training the RFR model. In addition, five subjects were invited to participate in the experiment on both user-dependent and user-independent [39]. The purpose of this study is to design an effective system for monitoring the effectiveness of toothbrushing. In previous work, we have studied and verified the feasibility of these two methods separately. In this study, we expanded on our previous work. Firstly, in order to build a complete toothbrushing monitoring system, we integrated both methods into a system, allowing for simultaneous detection of brushing region and brushing force. Secondly, in order to provide users with effective feedback, we used Unity to design a 3D tooth model, which communicates with the toothbrush device through TCP. By mapping the detection results in real-time onto the 3D tooth model, users can more intuitively understand their brushing situation. Finally, to validate the usability and performance of the system, we designed a user experiment and analyzed the experiment results. In the experiment, participants used our system to brush their teeth and answer the questionnaire after brushing, and the results showed that the system could detect toothbrushing region and brushing force well, with high user satisfaction and high performance. In summary, we want to provides a feasible solution for researching and designing more efficient, accurate, and reliable oral care tools.

III. SYSTEM DESIGN

For designing an intelligent toothbrushing system, there are three main issues: brushing regions detection, brushing force detection, and results visualization. Among them, brushing regions detection refers to determining the position of the teeth that the user is brushing using an inertial sensor. Brushing force detection refers to measuring the force applied by the user during brushing using a force sensor. Results visualization refers to presenting all the estimation results in a more intuitive way on the user interface, allowing the user to understand their brushing situation. In this chapter, we describe in detail how to implement each part individually.

A. APPLICATION MODEL DESIGN

In this research, we want propose a method that can detect brushing regions and brushing force in real time. As shown in Fig. 1, when users brush their teeth with a toothbrush with the force sensors and inertial sensor, data collected by the sensors can be used for regions estimation and force detection with the machine learning algorithm. In machine learning, we provide the computer with a large amount of toothbrushing data and allow it to find patterns on its own. The machine learning algorithm searches for patterns in this data and make decisions or estimations based on the patterns it finds. This process is accomplished through training, during which the algorithm continually tries to estimate results and adjusts its parameters based on actual results until estimations are sufficiently accurate. Finally, the estimation results can be displayed on the personal computer (PC) screen in real time.

In terms of machine learning algorithm, the Random Forest Algorithm is used to estimate brushing region and
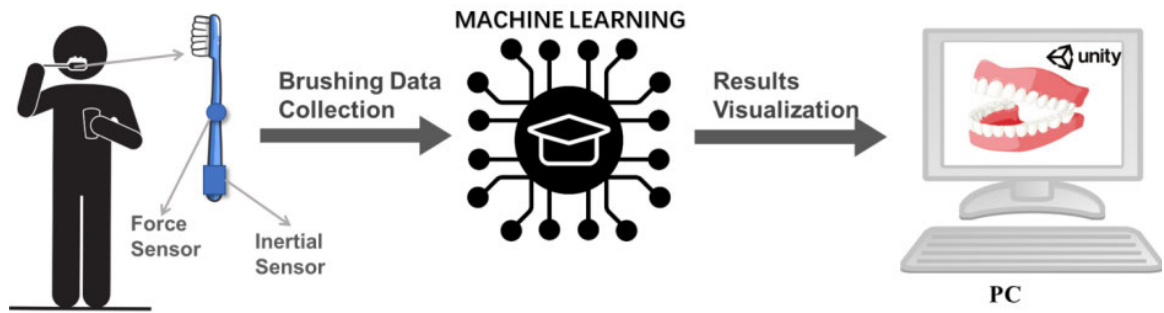
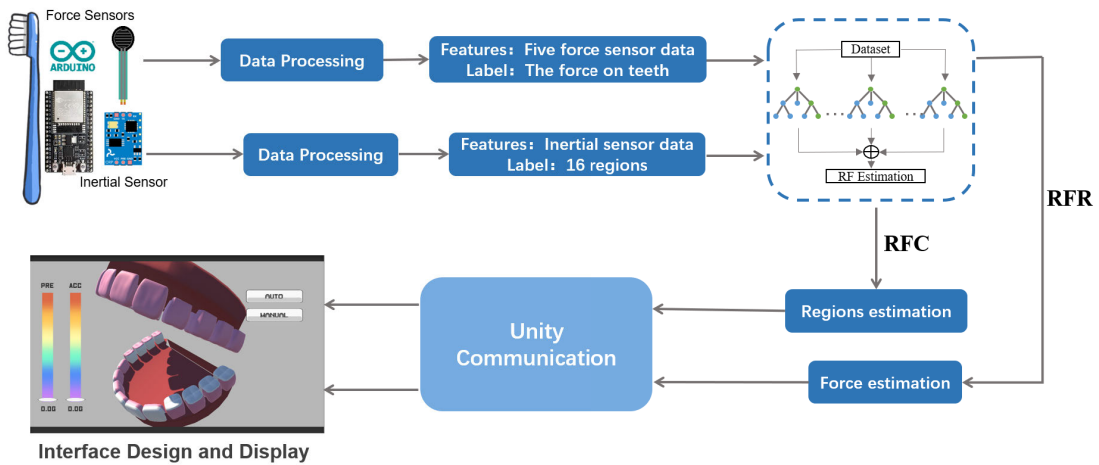**FIGURE 1.** Application model of smart toothbrushing system.

FIGURE 2. Structure of the 3D brushing monitoring system design.

brushing force. There are some advantages of Random Forest algorithm:

- It is a commonly used and easily implementable machine learning method.
- It has high classification and regression accuracy.
- It can handle multivariate data and avoid overfitting.
- It can estimate unknown data.
- It can automatically identify important features.
- It can handle a large amount of data and has good performance.

For detection of brushing region using inertial sensor, the RFC determines the classification results by randomly sampling the features in the dataset, constructing multiple decision trees, and finally voting on the results of all decision trees. In this study, inertial sensor can capture the dynamic data and features of each brushing region during the brushing teeth. The RFC can classify brushing region based on these information. As for the detection of brushing using FSR force sensor, the RFR can perform regression on the data by constructing multiple decision trees and combining the regression tree results to obtain more accurate estimation results. The FSR force sensor in this study can capture pressure data applied by the hand to the toothbrush during brushing process. The RFR can use these data and real force as lable to estimate brushing force.

The structure of the system design is shown in Fig. 2. We place force sensors on the toothbrush. The collected toothbrushing data is processed through Arduino and the processed data is transmitted to the computer, and the data from the five force sensors is used as features and the force on the teeth is used as the label for training the RFR model. Then, the corresponding estimated brushing force is output through the RFR model, and the result is finally visualized on the computer screen through communication with Unity. Similarly, the inertial sensor is placed on the toothbrush to collect action data during toothbrushing. After data processing in Arduino, the output value of the Euler angle is transmitted to the computer and used as a feature, and 16 toothbrushing regions are used as labels to train a RFC model. Then, the corresponding estimated result is output through the RFC model and displayed on the computer screen according to communicating with Unity. During this process, We used the clock of the same computer to achieve data synchronization and open-source algorithms from the library to process data. Two Arduino serial monitors were used to collect data from these two different sensors, with timestamp markings using clock source during data collection.

B. BRUSHING REGIONS DETECTION SYSTEM DESIGN
In this section, we will briefly introduce how to divide the regions for brushing teeth at first. According to the Bass
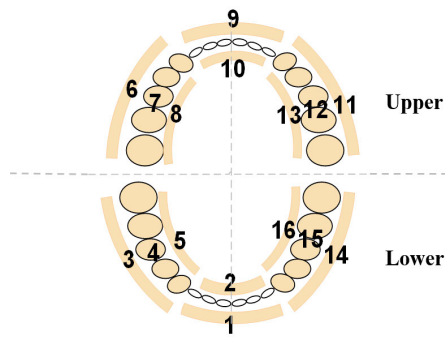
FIGURE 3. Structure of the 3D brushing monitoring system design.

Brushing Technique, each group of 2–3 teeth should be brushed around 15–20 times. Besides, many medical studies divide a person's teeth into 16 regions to check if brushing is comprehensive and effective. Generally, most adults have 32 teeth. Therefore, as shown in Fig. 3, these teeth are divided into 16 regions. For some special cases, such as tooth changes, as we divided 2-3 teeth into one area, the impact of tooth loss or change on the toothbrush area detection is relatively small. Even if a tooth is missing, the shape and position of this area will not change significantly.

As shown in Fig. 4, the system consists of a nine-axis inertial sensor placed on the handle of a toothbrush (Right-handed coordinate system), an Arduino board serving as the processor, a PC serving as the controller, and a 2D defined interface with 16 regions. When a person begins to brush their teeth, the system is activated. Firstly, the nine-axis inertial sensor placed on the toothbrush is used to obtain brushing action data. Secondly, according to the received data and filtering algorithms, the Arduino board can estimate the three Euler angles – yaw, roll, and pitch. Afterwards, the values of the three Euler angles are transmitted to the PC and used as features to train the RFC model. Finally, the trained model is used to estimat the brushing region and the estimation result is displayed in real-time on the PC screen.

1) TWO ALGORITHMS FOR ONLINE REGION DETECTION
a: ALGORITHM BASED ON RFC MODEL
For the online region detection algorithm, we proposed two methods, one of which is the RFC model based on machine learning algorithm, the flow chart of which is shown in Fig. 5(a). The system restarts after training and verification of the RFC model. When a person starts to brush their teeth, the data of brushing actions will be collected through the nine-axis inertial sensor and then the Arduino calculates the three Euler angles and transmits them to the PC. Next, the trained RFC model is imported for teeth brushing Regions classification. Finally, the estimation results can be displayed online in real-time on the PC screen.

b: ALGORITHM BASED ON MANUAL THRESHOLD DEFINITION
In order to test the accuracy of the RFC mode classification recognition algorithm in detecting the brushing regions,

we also propose another algorithm that requires manually defining thresholds to determine the brushing regions. The position of the brushing is determined by the roll and pitch angles to a large extent based on the orientation information of the brushing. The algorithm flowchart is shown in Fig. 5 (b). Using the data obtained from the nine-axis sensor when brushing the teeth, the maximum and minimum values of the roll and pitch angles of each region are used as thresholds to determine the range. Based on which range the values of the roll and pitch angles belong to, the position of the brushing is determined, and the estimated result also can be displayed on the PC screen. This method can also estimate the brushing regions in real-time online.

C. BRUSHING FORCE DETECTION DESIGN
1) SYSTEM MODE
As shown in Fig. 6, the hardware of this system consists of a toothbrush, an electronic balance, five force sensors, an Arduino circuit board, and a PC. When the subject uses the toothbrush with five FSR sensors fixed on the handle to simulate brushing on the electronic balance, the electronic balance measures the force generated during the brushing and transmits the measurement data to the PC as the label. At the same time, the five sensors collect information on the change in force of the toothbrush during the brushing, and these data are collected by the Arduino software as features for the RFC model. Finally, all collected data are used to train and test the RFC model and evaluate the accuracy of the estimated results.

2) FORCE SENSITIVE RESISTOR (FSR) SENSOR
The FSR sensor is a common type of pressure sensor that is widely used in various industries. FSR sensor has the advantages of small size, high sensitivity, low cost, and ease of use. Therefore, it has been widely used in automation control, human-machine interaction, pressure measurement, and force detection. The working principle of FSR sensors is to control the change in resistance value by measuring pressure applied to the sensing area. When applied pressure increases, the resistance value of the FSR sensor decreases; when applied pressure decreases, the resistance value of the FSR sensor increases. The change in resistance value causes the output voltage value to also change, so we can get the relationship between the output value of the FSR force sensor and the force value, as shown in Fig. 7.

The placement of FSR sensors is usually in places where pressure changes need to be monitored, as shown in Fig. 8. The specific information of the FSR sensor that we used in this experiment is as follows:

- Manufacturer number: MF01-N-221-A04
- Force sensitivity range: 10 g – 1000 g
- Force repeatability: ± 5%
- Response time: < 1 ms

3) PRINCIPLE OF INDIRECT BRUSHING FORCE DETECTION
As shown in Fig. 9 and (1), F_1 is the brushing force; F_2 are the force applied by the hand to the toothbrush. According to the principle of leverage, There is a good correspondence
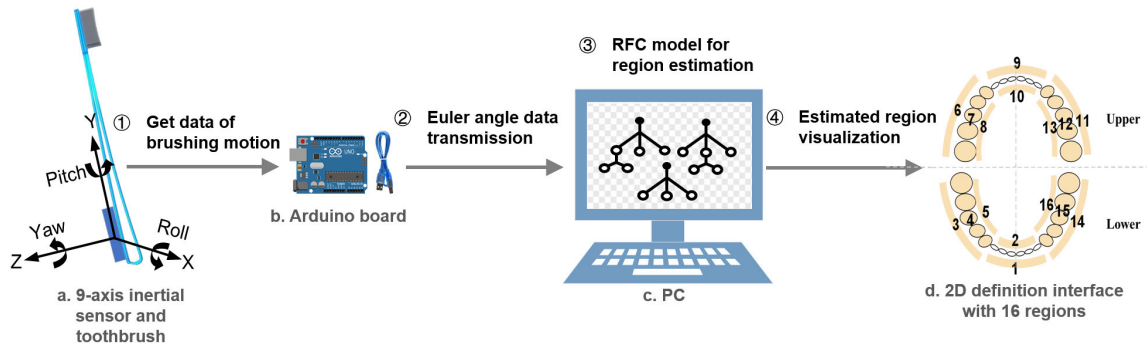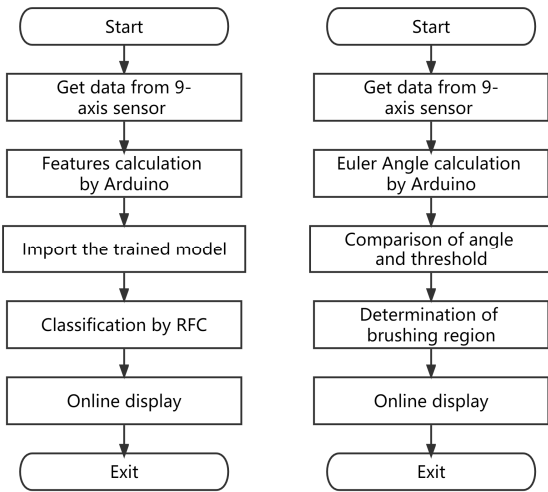
FIGURE 4. Structure of the system for brushing region detection.

(a) Algorithm based on RFC model (b) Algorithm based on RFC manual threshold definition

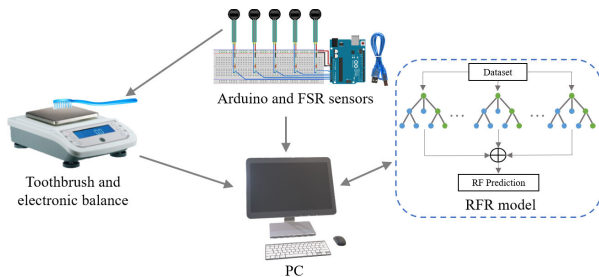**FIGURE 5.** Flow chart of algorithm for online region detection.

FIGURE 6. The structure of the system for brushing force detection.

FIGURE 7. Relationship between force value and sensor output value.
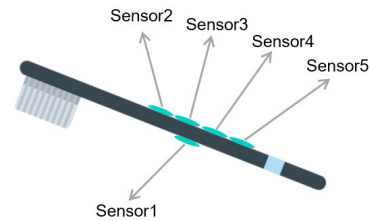
FIGURE 8. FSR Sensor placement.
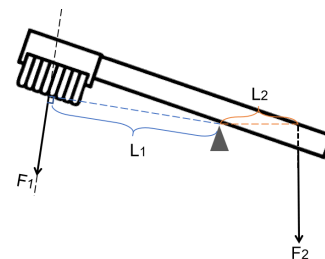
FIGURE 9. Simple analysis of brushing force.

between F_1 and F_2, so the proposed method of this study can estimate the brushing force (F_1) indirectly by collecting forces (F_2) data applied by the hand to the toothbrush.

$$F_1 \cdot L_1 = F_2 \cdot L_2 \tag{1}$$

4) TWO TRAINING ALGORITHMS FOR FORCE DETECTION
a: USER-DEPENDENT TRAINING ALGORITHM
User-dependent training methods require training data from each user, from which user-specific models are generated.
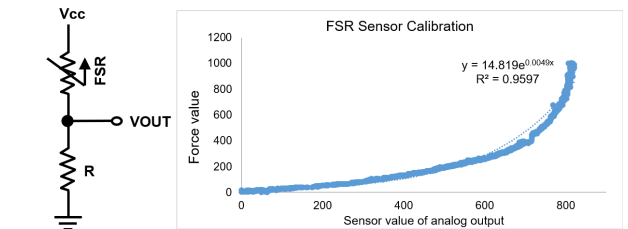
As shown in Fig. 10 (a), input the dataset for each subject. First, 75% of the samples are used for training the model; 25% of the samples are used for testing. Second, Grid Search cross-validation is used to select the best RFR model. Third, we can know the importance of each feature to the model through feature importance analysis. Fourth, visualize the true value and estimated result plots. Finally, calculate the RMSE of the model.

b: USER-INDEPENDENT TRAINING ALGORITHM
User-independent training methods require training data from multiple participants and generate a common model or user-independent model that can be applied to other users.
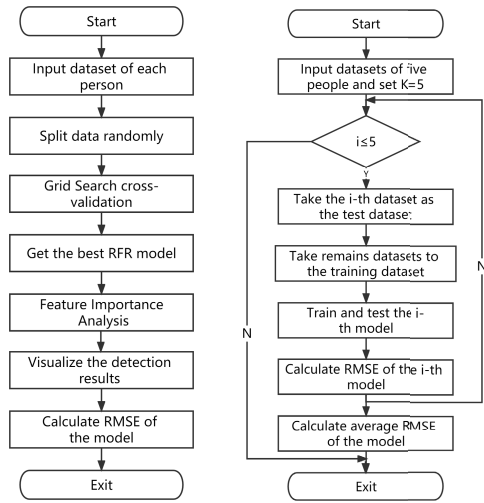
(a) User-dependent training algorithm based on RFR

(b) User-independent training algorithm based on RFR and Leave One Out Cross-Validation (LOOCV) method

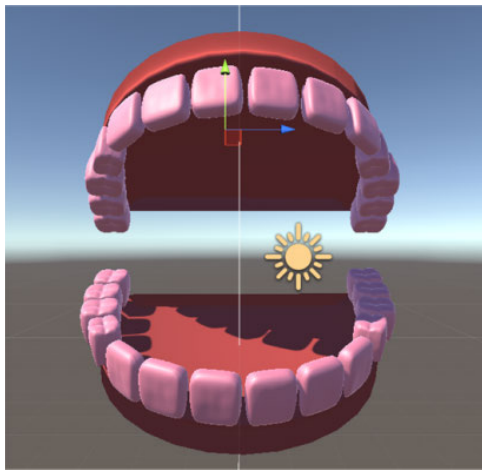**FIGURE 10. Flow chart of algorithm for force detection.**

FIGURE 11. Visual user interface based on Unity.

As shown in Fig. 10 (b), the Leave One Out CrossValidation (LOOCV) method is used to train and test the RFR model. First, input the datasets of all subjects and then traverse all datasets; take one dataset as the testing dataset and the remains datasets as the training dataset; train each model with the training dataset and use the testing dataset to calculate the RMSE of each model. Finally, calculate the average RMSE after finishing the traversal.

D. 3D VISUALIZATION WITH UNITY
1) VISUAL USER INTERFACE DESIGN

For designing a simulated teeth brushing user interface, we chose to use the Unity development environment. Unity is an application designed specifically for game development, providing a rich set of graphics and physics engines that can easily implement complex simulation functions. In this
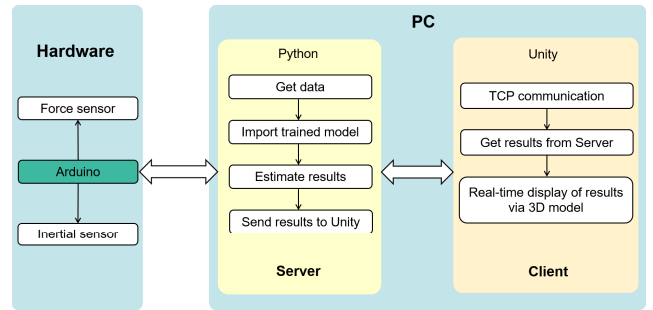

FIGURE 12. Communication diagram between Arduino, Python, and unity.

research, as shown in Fig. 11 we used Unity's graphics engine to create a simulated teeth brushing user interface. Firstly, we designed a simple 3D teeth model using Unity. The tooth model was divided into 16 regions as required by the research in order to evaluate the accuracy and stability of brushing. The initial color of the teeth was set to pink and the color of the related region will be changed when it was brushed. This allowed users to more intuitively and clearly understand the feedback information through the changes in the color of the related region during brushing.

2) COMMUNICATION METHOD

Fig. 12 shows the communication between the controllers. Firstly, Arduino sends data received from the force sensor and the inertial sensor to the Arduino software on the PC. Next, Python reads the data from Arduino and imports the trained model to estimate the region and Force. Then, Python creates a server. Unity, as a client, connects to the server by TCP communication. After the connection is made, Python sends the estimation results to Unity. Unity receives the data and uses scripts, written in a programming language such as C#, to specify behavior of the model. In this way, with the Unity development environment, we were able to create a highly realistic simulated teeth brushing user interface that provides users with a better teeth brushing experience and feedback.

3) VISUALIZATION DESIGN OF REGION AND FORCE DETECTION RESULTS

The design of the visualization function is shown in Fig. 13. After successful communication between Python and Unity, Unity gets the detection results of the brushing region and brushing force. Dental clinic professionals suggest that the appropriate brushing pressure is between 100 g–200 g. Therefore, if the force is less than 100 g, the region will turn yellow to prompt the user that the brushing force is too light; if the force is less than 100 g and greater than 200 g, the region will turn green to prompt the user that the brushing force is appropriate; if the force is greater than 200 g, the region will turn red to prompt the user that the brushing force is too hard. When the user brushing this region over 15 seconds, this region turns white to indicate that the region has been brushed effectively. In this way, the user can clearly and intuitively understand the feedback information while brushing.
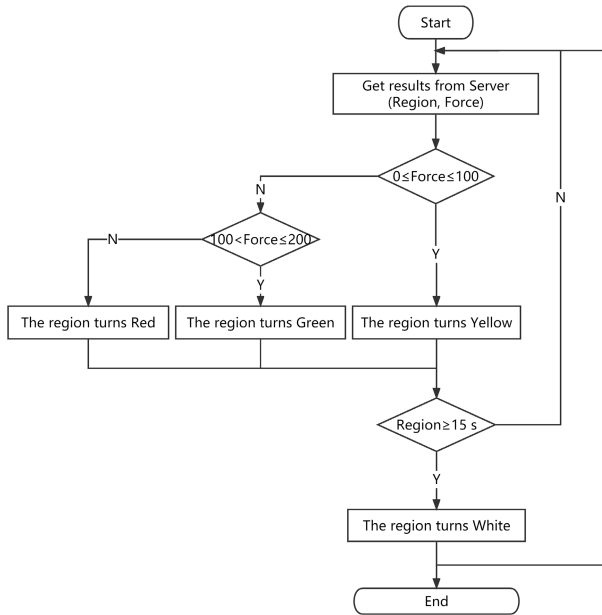
FIGURE 13. Flow chart of the detection results visualization function.

FIGURE 14. Regions classification with RFC model.

the Arduino serial port data (three Euler angles). Throughout the entire brushing process, we found that the Euler angles changed as the brushing region changed.

3) TRAINING AND VALIDATION OF RANDOM FOREST CLASSIFIER MODEL

Fig. 14 shows the framework of the RFC classification algorithm. The three Euler angles estimated by Arduino with the data getting from the IMU sensor are used as features for training the RFC model. We collected a total of 7578 sets of samples, of which 5683 (75%) samples are used to train the model and 1895 (25%) samples are held back for verification. Finally, the 743 samples are used to test and estimate the brushing regions online with the trained model.

RFC as the pattern classification recognition algorithm, consistent with a large number of individual decision trees. Each tree in the random forest spits out a class estimation and the class with the most votes become the model's estimation result. In the process of training the model, a grid search algorithm is used to find better parameters to improve the model and there are three important parameters: n, m_f, and m_d. The n is the number of sub-datasets generated by sampling the original data set with replacement, that is the number of decision trees; the m_f is the maximum number of features considered when constructing a better model for decision-making; the m_d is the maximum depth of the decision tree. The parameters in this model are m_d: 7; m_f : 0.6; n: 100. The model corresponding to these parameters is used as the trained model for identifying the brushing regions. Different people will get a different model which is suitable for themselves according to their brushing posture and habits. In addition, as shown in Fig. 15, we visualize one of the decision trees after training the RFC model. It can estimate the brushing region by learning simple decision rules inferred from data features.

Regarding the decision rules, at each node, the decision tree automatically searches for the value to be split among the elements to minimize the Gini coefficient. In essence, the Gini index is a measure of variance. The higher the variance, the more mis-classification there is. Therefore, lower Gini Index can yield better classification. Besides, samples means the number of samples remaining at that particular node; valves means the number of samples of each class remaining at that particular node and sum of values at a node more than samples

IV. EXPERIMENT AND EVALUATION

A. BRUSHING REGIONS DETECTION EXPERIMENT DESIGN

1) EXPERIMENT SETTING

In this study, we use the MPU9250 sensor to detect the brushing regions. MPU-9250 is a 9-axis motion tracking device that combines a 3-axis gyroscope, 3-axis accelerometer, 3-axis magnetometer, and a Digital Motion Processor (DMP)-MPU9250. The open-source Madgwick filter algorithm was used for sensor fusion, noise suppression, and attitude estimation. The Arduino library for IMU sensors allows us to read the values of the accelerometer, magnetometer, and gyroscope from the MPU9250 sensor. The pitch and roll angles can be calculated from data collected by the accelerometer, but if we use the gyroscope to calculate the yaw angle, initial orientation angle bias and the gyroscope bias and drift bring another complexity to our application. Therefore, in order to reduce error, the toothbrush should be placed on a horizontal surface and wait for the data to stabilize after turning on the system for a while. The sampling rate of the 9-axis sensor is 200 Hz.

2) DATA COLLECTION

In this study, the subject brushed her teeth under the brushing sequence and method of Bass Brushing Technique. In order to better observe the participants' brushing posture, we placed a mirror in front of the participant. The participant was instructed not to move or rotate their head while brushing, and to maintain movement in each brushing region for 10 seconds. To collect data and perform signal processing and analysis, we utilized a processor to transfer the data from the brushing process to the processor. Finally, we employed a python algorithm to real-time online acquire the data through reading
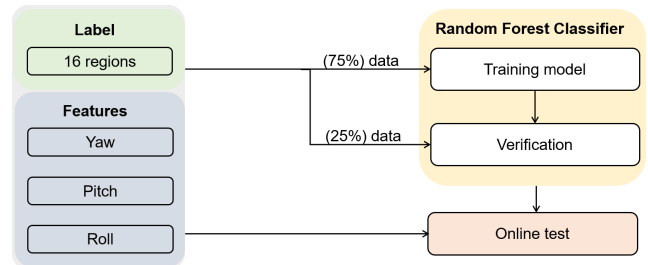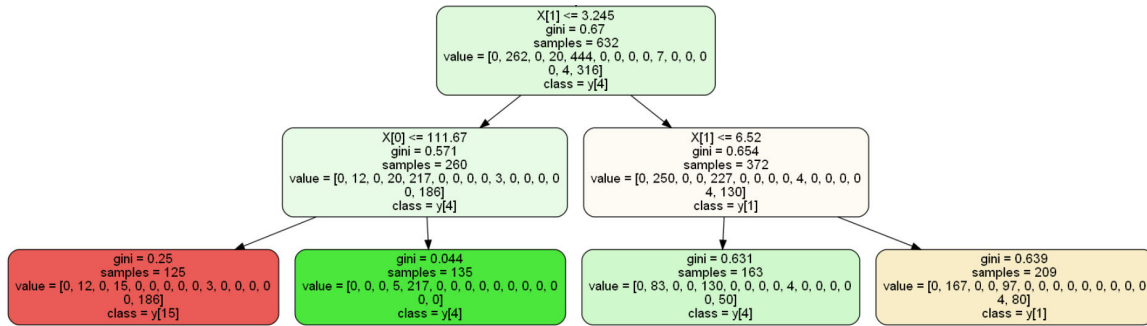
FIGURE 15. A part of one of the decision trees to show the automatic threshold definition.

because random forest works with duplicates generated by bootstrap sampling; class is the estimation result.

In addition, the SHAP method was employed to elucidate the feature contributions. Specifically, concerning the RFC model, as illustrated in Fig. 16, The features are evenly distributed in the dataset, indicating a relatively balanced impact of features. Each feature demonstrates nearly equal contributions to the prediction of the brushing region.

Finally, the trained model will be used to identify the brushing regions. Following Fig. 17 shows the estimation results of the brushing regions after classifying the data getting from one of the subjects. We collected a total of 7578 samples from the subject. 1895 (25%) samples were used for verification, and the verification accuracy was 97.6%, which shows that it is possible to classify the different brushing regions with high accuracy using only Euler angles as the feature vector.

4) ACCURACY EVALUATION

We evaluate "Contribution of each feature" and "Difference of identification accuracy by changing combination of features". Here, we used accuracy rate (*AC*) as identification accuracy:

$$AC = \frac{a}{b} \times 100\% \qquad (2)$$

where *a* means the number of data correctly identified; *b* means the total number of data.

In the field of machine learning, confusion matrices are widely used to evaluate the performance of a classifier. For the RFC algorithm, the confusion matrix in Fig. 18 shows that 2, 4, 6, 8, 13 regions can be perfectly identified for the dependent user, the accuracy of 3, 7, 10, 11, 14 regions are more than 80% which is good and the accuracy of other 6 regions are less than 80% which is bad. In the event that a true region is estimated as a false region, there are typically two reasons for this error. Firstly, the actions of brushing teeth in the true region and false region are similar, causing the collected dynamic data to also be similar. This similarity leads to estimating real region as false region. For example, for region 1, evaluation accuracy of true region (region 1) is just 6.7% and evaluation accuracy of false region (region 9) is 48.2%. That's because the two regions are very similar. Secondly, inertia sensor need to be placed in the same horizontal

position for calibration each time. If the placement position during calibration is changed, the real-time data collected will be different from the data used to train the model, also leading to the false region being estimated. In general, The online estimation average accuracy is 74.0% in this system and the model performs well although has difficulty with the lower (1) and upper (9) front of the incisors which can be improved by using good features.

For another algorithm of manual threshold definition, the confusion matrix in Fig. 19 shows that just the 4, 14, 14 regions can be perfectly identified, 4 regions detection accuracy is more than 80% and other 9 regions detection accuracy is less than 80%. The evaluation accuracy of this method is also affected by similar brushing action and calibration of inertial sensor, such as region (2). Evaluation accuracy of true region (region 2) is just 0% and evaluation accuracy of false region (region 10) is 80.9%. In general, the online estimation average accuracy is 62.7%, which is about 11.3% less than the accuracy of the RFC online detection method. Therefore, the experimental results show that the accuracy of the RFC algorithm is better than the algorithm of manual threshold definition for online real-time detection of toothbrushing regions.

B. BRUSHING FORCE DETECTION EXPERIMENT DESIGN

1) EXPERIMENT SETTING

- **Presumption:** It is assumed that the position of the finger should be fixed so that the force point of the finger is within the sensing area of the sensor.
- **Experiment Setup:** The electronic balance is placed horizontally on the table and is connected to the computer through the RS-232 interface. The five force sensors connected with the Arduino are stuck to the handle of the toothbrush. One is in the same direction as the bristles and the other four are in the opposite direction.
- **Experimental Process:** Before the experiment, the subjects were instructed how to do this experiment. First, the subject sits in front of the table where electronic balances and toothbrushes were placed. Second, the subject picks up the toothbrush with the right hand and places five fingers on the corresponding sensing area of five force sensors. Third, the subject begins to simulate the action
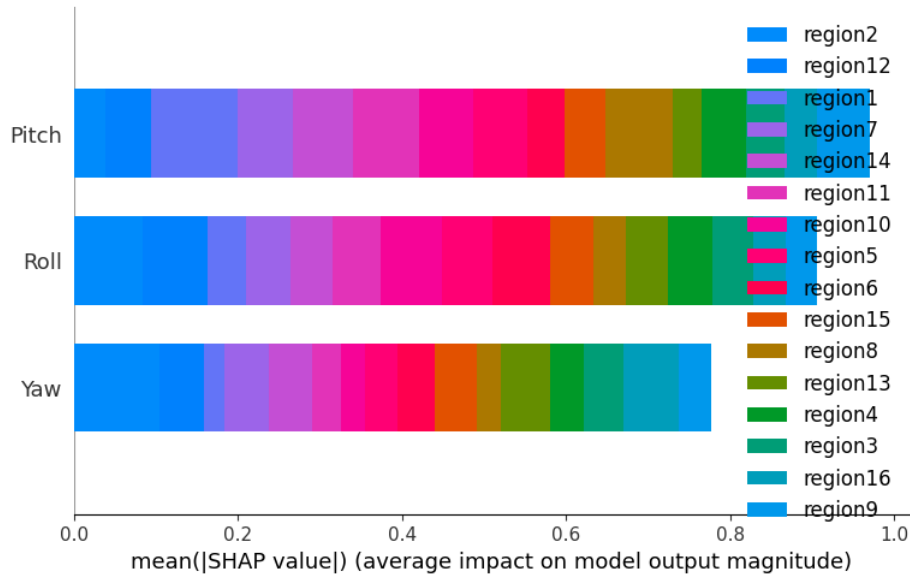
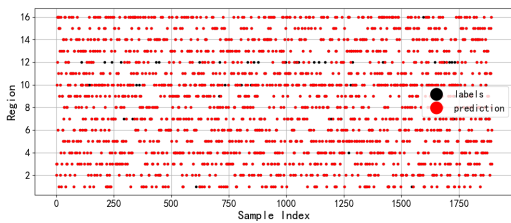**FIGURE 16.** Feature contribution of RFC model using SHAP method.

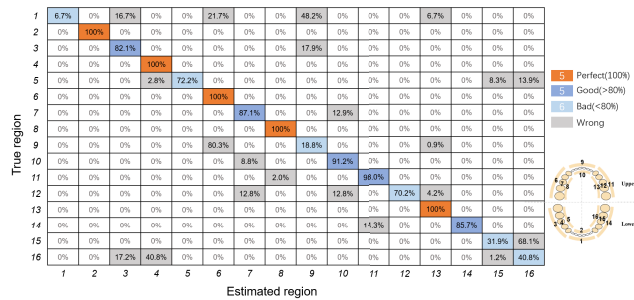**FIGURE 17.** RFC verification results.

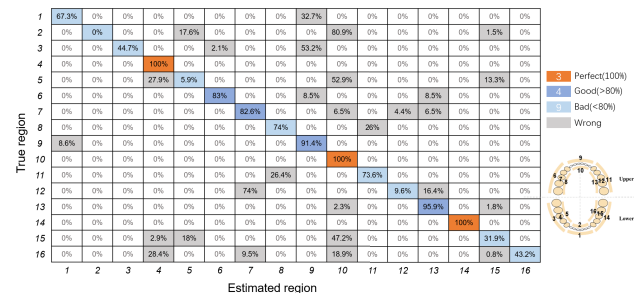**FIGURE 18.** RFC confusion matrix for online test.

FIGURE 19. Confusion matrix of manual threshold definition for online test.

of brushing their teeth horizontally on the electronic scale. Fourth, the subject is asked to repeatedly brush the

electronic balance with the force slowly changing from 0 g to 300 g for about 3 minutes.

2) DATA COLLECTION

Five subjects were invited to participate in the experiment and they were all right-handed. To collect data, we used RsWeight software to collect weighing data and Arduino to collect force sensor data. The serial port rate of RsWeight and Arduino was set to 115200 bps and the sampling frequency to 7.5 Hz. When we pressed the start button, both the weighing data and force sensor data were transferred to the PC simultaneously and synchronized using the same real-time clock (RTC). This allowed us to understand the behavior and actions of the participants in the experiment through the analysis of the weighing data and force sensor data.

3) TWO TRAINING ALGORITHM BASED ON RANDOM FOREST REGRESSION

We designed two algorithms based on the RFR method to estimate the brushing force, evaluate the estimation results, and compare the performance difference between user-dependent and user-independent. User-independent represents each data point as independent from other data points, while user-dependent data represents each data point as having an impact on other data points.

4) RANDOM FOREST REGRESSION MODEL

Regarding the parameters of the RFR model, Grid Search cross-validation is also used to select the best parameters and RFR model. For subject C, the parameters of RFR model are m_d: 7; m_f: 0.8; n: 200; for subject D, the parameters of RFR model are m_d: 7; m_f: 0.6; n: 200. In addition, for features contribution, as shown in Fig.20, sensor 2 is the most important feature, contributing significantly to the prediction
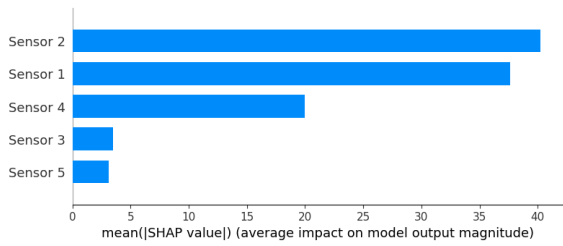
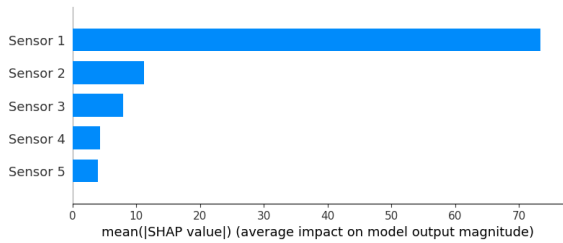**FIGURE 20.** Feature contribution of RFR model of subject C.

FIGURE 21. Feature contribution of RFR model of subject D.

TABLE 1. The results of user-dependent training.

Subjects	Gender	Age	RMSE (g)
A	F	24	19.7
B	F	28	27.3
C	M	27	14.1
D	M	24	28.6
E	F	23	20.7
Mean	-	-	22.08
SD	-	-	5.94

results. Additionally, while the influence of other features on the results may not be very pronounced, they still contribute to the model's improved predictive performance. However, as shown in Fig. 21, for another subject, sensor 1 is the most important feature, contributing significantly to the prediction results. Therefore, individuals may hold toothbrushes and apply forces differently, resulting in varying feature contributions. This leads to individual differences in the feature importance when using the RFR method to detect toothbrushing force.

5) RESULTS ANALYSIS
a: RESULTS OF USER-DEPENDENT TRAINING
For user-dependent training, as shown in Table 1, the average RMSE is 22.08 g and the SD is 5.94 g. Also, the relative error is 7.36% when the detected brushing force reaches the maximum value (300 g). This result indicates that the proposed method has good estimation accuracy within the range of force testing (0 g–300 g) and is capable of achieving its goal of detecting brushing force. Fig. 22 is the estimated results with the smallest RMSE (14.1 g) and Fig. 23 is the estimated results with the largest RMSE (28.6 g) among the five subjects. As shown in the following figures and Table 1, estimation results of each person is different. This is because everyone has different toothbrush postures and toothbrush holding habits to a large extent. Moreover, changes in
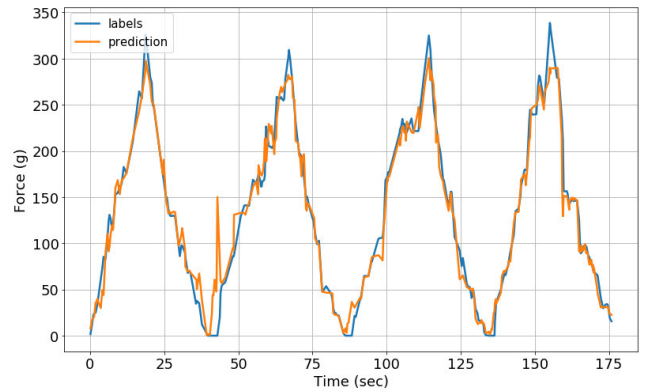

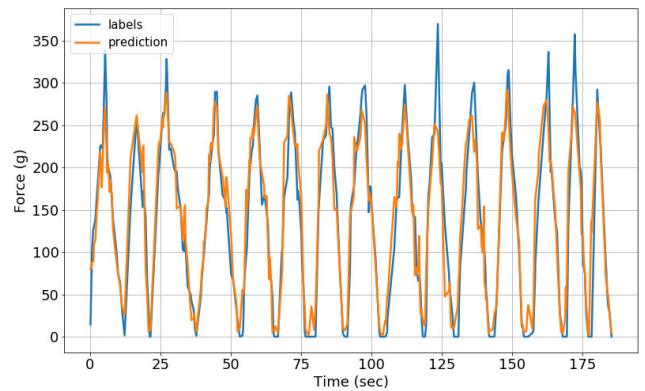**FIGURE 22.** Brushing force estimation results of subject C.

FIGURE 23. Brushing force estimation results of subject D.

TABLE 2. The results of user-independent training.

Testing Dataset	Training datasets	RMSE (g)
A	BCDE	32.8
B	ACDE	30.4
C	ABDE	43.8
D	ABCE	42.5
E	ABCD	35.8
Mean	-	37.06
SD	-	5.90

brushing posture can also reduce the accuracy of the estimation results during the simulated brushing process. For example, subject D moved the position of her finger during the simulated brushing process, which caused some areas to deviate from the sensing area of the sensor and reduce the accuracy of the estimation results.

b: RESULTS OF USER-INDEPENDENT TRAINING
As one would expect, the training method for user-independent is consistently inferior to that for user-dependent when all else is equal. As shown in Table 2, the average RMSE is 37.06 g and the SD is 5.90 g; the average RMSE increased by 14.98 g and the SD reduced by 0.04 g compared to user-dependent; the relative error is 12.35% when the detected brushing force is 300 g. In addition, the RMSE exceeded 40 g when the data of subject C and subject D were used as the testing dataset respectively and the data of other subjects were used as the training dataset. This indicates that
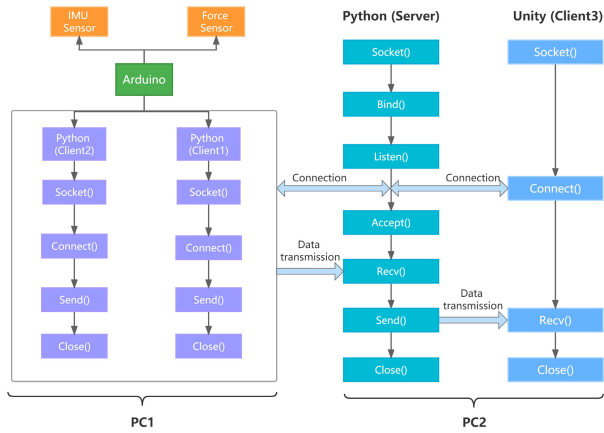
FIGURE 24. State diagram for Server and Clients communication with TCP socket.

the data of these two subjects and the data of other subjects are so different that their data cannot be estimated well by the user-independent model. It can be concluded that this indirect method of detecting the brushing force has a larger user correlation.

C. USABILITY EXPERIMENT

1) COMMUNICATION WITH UNITY

After obtaining the estimation results of the brushing region and force, the next step is to transfer the estimation results to Unity and display them through the 3D model. There are many methods to choose from when communicating between Python and Unity. The most commonly used methods include calling Python scripts in Unity, calling Unity functions in Python, using network communication, and using file communication, etc. In this research, we choose network communication. This method can be implemented using sockets. We can establish a connection between Python and Unity and communicate over the connection. The advantage of this method is its flexibility, it is not limited by the platform, and it can be easily extended.

As shown in Fig. 24, when Python as the server and Unity as the client in communication, the interaction between them is as follows:

- In Python, a socket is first created and bound to an IP address and port. This allows the server to be accessed through this IP address and port.
- The "listen" function is then used to start listening for connection requests. This allows the server to wait for client connections.
- In Unity, a socket client is created and the "Connect" function is used to initiate a connection request to the server. This allows the client to connect to the server.
- In Python, the server uses the "accept" function to accept the client's connection request. This establishes a connection between the server and the client.
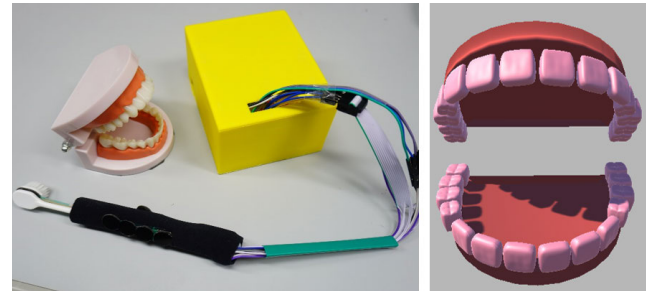- Then the server and the client can communicate and exchange data through this connection. In Python, the

FIGURE 25. 3D brushing monitoring system of this research with the User Interface designed by Unity.

server can use the "Send" function to send data to the client. In Unity, the client can use the "Recv" function to receive data from the server.
- After the communication is complete, the connection between the two can be closed using the "close" function.

2) USABILITY EXPERIMENTAL ENVIRONMENT SETUP

In this study, we aimed to improve the stability, reliability, and efficiency of our system by setting the same re-sampling frequency to 2Hz. Specifically, reducing the sampling frequency helps to transmit data to Unity more stably by avoiding discontinuities and data loss caused by delays in data transmission. Moreover, it also reduces the amount of data and the bandwidth and computing resources required for data transmission, thereby enhancing the system's performance. To get the integrated data, we used two Arduino serial ports to read data from the nine-axis sensor (Euler angles) and the pressure sensor (voltage conversion value corresponding to pressure), respectively, with the same re-sampling frequency. We then aligned these data using the clock system of the same computer and transmitted the acquired data in real-time to Python to train the RF model and obtain corresponding prediction results. Finally, we transmitted the prediction results in real-time to Unity for a more comprehensive display.

In the previous work of this research, we conducted experiments on detection of brushing regions and force detection, and implemented the transfer of relevant detection results to Unity for displaying. Next, we need to conduct usability experiments on the 3D brushing monitoring system. In order to evaluate performance and satisfaction of the new 3D brushing monitoring system. To achieve this goal, we designed a questionnaire to measure participants' perceived satisfaction with this system. The questionnaire consists of 8 questions about daily toothbrushing, covering various aspects of the system, including usability, accuracy, information quality, interactivity, etc. Participants were asked to answer the questionnaire after completing the experiment. The results of this experiment will provide valuable feedback for further improvements of this system.

- 20 participants was invited to participate in this experiment.

- Participants simulated brushing activities on the tooth model using corresponding devices.
- Brush each region evenly from 0 g to 300 g.
- Each region lasts about 10 seconds.
- Participant fills out a usability questionnaire after completing experiment.

3) USABILITY RESULTS EVALUATION

As shown in Fig. 25, we simplified the experimental device. To make the system device more user-friendly, we designed and manufactured a casing on the handle of the toothbrush and embedded force sensors and inertial sensors inside of it. Additionally, we used 3D printing technology to print a small box to hold all circuit connection components to make the entire circuit connection system more stable and concise. Furthermore, the tooth model was fixed on the table to simulate brushing activity and a PC was placed on the table to visualize the detection results. In this paper, we improved the Unity model, as shown in Fig. 26, by using changes in tooth color to display real-time brushing region and force detection results, and the perspective can automatically switch to the current brushing region for clearer observation.

4) USABILITY EXPERIMENT PROCEDURE

The purpose of the usability experiment is to evaluate performance and satisfaction of the new 3D brushing monitoring system. To achieve this goal, we designed a questionnaire to measure participants' perceived satisfaction with this system. The questionnaire consists of 8 questions about daily toothbrushing, covering various aspects of the system, including usability, accuracy, information quality, interactivity, etc. Participants were asked to answer the questionnaire after completing the experiment.

When asked about toothbrushing frequency among 20 participants, 80% of them reported brushing their teeth at least twice a day, while 20% reported brushing once a day. This indicates that brushing teeth is an important habit in daily life. In addition, as shown in Table 3, 70% of participants had used an electric toothbrush. Among these users, 85.71% reported that their electric toothbrush did not have toothbrush region detection and user interface and 64.29% reported that their electric toothbrush did not have brushing force detection. This suggests that while some electric toothbrushes on the market can detect brushing region and force, they are relatively expensive, and most people's electric toothbrushes do not have these functions.

Table 4 and Fig. 27 present statistical results when participants were asked about the factors that would affect their willingness to use a toothbrushing system. Firstly, the goodness of fit test did not show significance ($\chi 2=2.500$, $p=0.475>0.05$), indicating that the proportion of choices was relatively uniform and there was no significant difference. Secondly, from the analysis of the popularity rate and response rate, it can be seen that the most considered factor was price, followed by useful brushing feedback information, ease of use of the system, and intuitive user interface. More

than half of the participants will consider the price, information quality, and usability of a toothbrushing system.

Question 5 comprises 8 statements is used to evaluate performance and satisfaction of this system and it follows a 5-point Likert Scale. Participants were asked to choose one option from 5 available options for each statement, including strongly agree (5 points), agree (4 points), neutral (3 points), disagree (2 points), and strongly disagree (1 point). Participants were required to rate these statements after using this system. The 8 statements are as follows:

1. It had good accuracy for detecting brushing region.
2. It had good accuracy for detecting brushing force.
3. This system has good visual consistency in the layout and components of the user interface.
4. The information (such as online detection, on-screen messages, and other documentation) provided with this system was clear and instructive.
5. I liked using the interface of this system. The interface is clear, intuitive and interactive.
6. This system is helpful for my teeth health.
7. It was simple to use this system.
8. Overall, I am satisfied with this system.

According to Table 5, the KMO value is 0.621, which falls between 0.6 and 0.7, indicating that the research data is appropriate for information extraction. The reliability coefficient value is 0.825, which is greater than 0.8, indicating that the research data has high reliability quality. As shown in Table 4 and Fig. 28, participants provided positive evaluations of the system. They considered the system to have good detection accuracy, information quality, interactivity, usability, performance, and satisfaction. However, regarding Statement 1 on the accuracy of region detection, the evaluation score was below 4. This may be due to different brushing positions of different individuals, which could result in errors in region detection. However, collecting more data can effectively improve this issue.

In response to questions about whether this system could help improve their brushing effectiveness and whether they would recommend our toothbrush system to their family and friends, 100% of participants believed that the system could effectively improve their brushing and 95% of them were willing to recommend the system to their family and friends. This indicates that the system has achieved its goal of helping people improve their brushing effectiveness and maintain dental health. Furthermore, people's high ratings for the system's performance and satisfaction demonstrate its strong practical value.

5) USABILITY COMPARISON EXPERIMENT

In this paper, we integrated region detection, force detection, and Unity visualization into a complete system, in addition to the usability experiments we conducted in this study. Furthermore, we also conducted two other comparative usability experiments using Philips electric toothbrush and Oral-B electric toothbrush. In this way, we can evaluate the

TABLE 3. Statistical results on electric toothbrush questions (n is sample of participants).

| Items	Categories	n	Percent (%)	Cumulative Percent(%)
Have you ever used an electric toothbrush (n=20)	no	6	30.00	30.00
	yes	14	70.00	100.00
Whether there is brushing region detection (n=14)	no	12	85.71	85.71
	yes	2	14.29	100.00
Whether there is user interface (n=14)	no	12	85.71	85.71
	yes	2	14.29	100.00
Whether there is brushing force detection (n=14)	no	9	64.29	64.29
	yes	5	35.71	100.00
Total		20	100.0	100.0
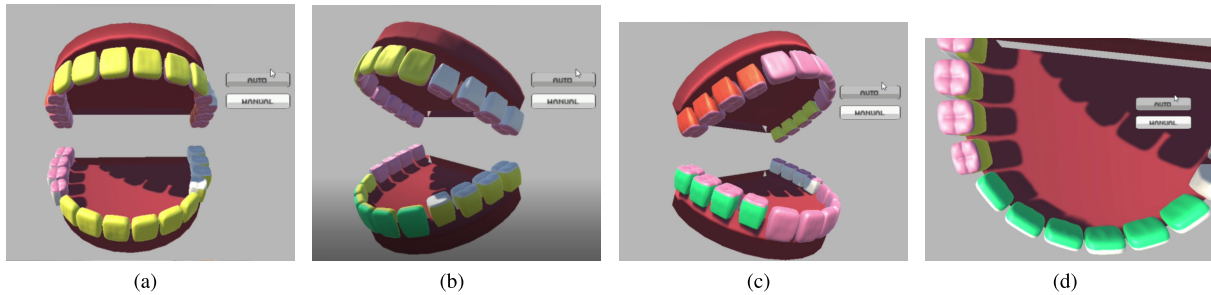
FIGURE 26. The perspective can be automatically switched. (a) is front perspective, (b) is right perspective, (c) is left perspective, (d) is down perspective.

TABLE 4. Statistical results on factors in the willingness to use a toothbrush system (n is sample of participants).

Categories	Response		Popularity rate (n=20)
	n	Response rate	
Price	15	31.25%	75.00%
Ease of use of the system	11	22.92%	55.00%
Useful brushing feedback information	14	29.17%	70.00%
Intuitive user interface	8	16.67%	40.00%
Total	48	100%	240.00%

$\chi 2 = 2.500$, $p = 0.475$
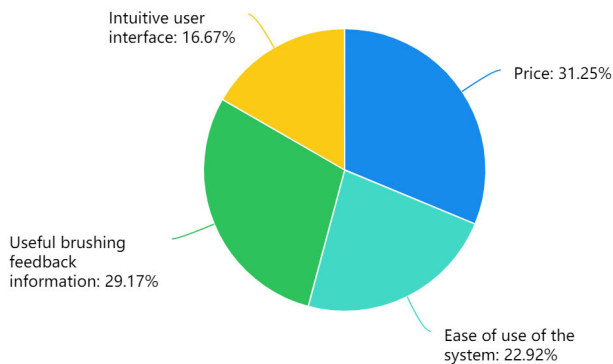
FIGURE 27. Response rate of 20 subjects of factors in the willingness to use a toothbrush system.

TABLE 5. Statistical results on 8 statements about this toothbrushing system performance (n is sample of participants, SD is standard deviation).

Statements	n	Min.	Max.	Mean	SD	Median
1	20	3	5	3.95	0.510	4.0
2	20	3	5	4.10	0.718	4.0
3	20	3	5	4.25	0.716	4.0
4	20	4	5	4.40	0.503	4.0
5	20	3	5	4.35	0.671	4.0
6	20	4	5	4.60	0.503	5.0
7	20	3	5	4.50	0.688	5.0
8	20	3	5	4.45	0.605	4.5
KMO				0.621		
Bartlett's Test of Sphericity				76.769		
p				0.000		
Cronbach α				0.825		

FIGURE 28. Average point and Standard Deviation of 20 subjects for 8 statements of this toothbrushing system. Every statement starts with 5 (strongly agree) and ends with 1 (strongly disagree). The higher the score, the better the performance and satisfaction.

effectiveness and efficiency of the system in comparison with existing brushing products. The results of this experiment will provide valuable feedback for further improvements of this system. As shown in Fig. 29, we designed three groups of experiments. Group A and Group C consist of two kind of electric toothbrushes, tooth model, and corresponding APP(provided visual interface). Group B is the 3D brushing monitoring system designed in this research.

As shown in the figure, we simplified the experimental device. As shown in Fig. 29, we designed three groups of experiments. Group A and Group C consist of two kind
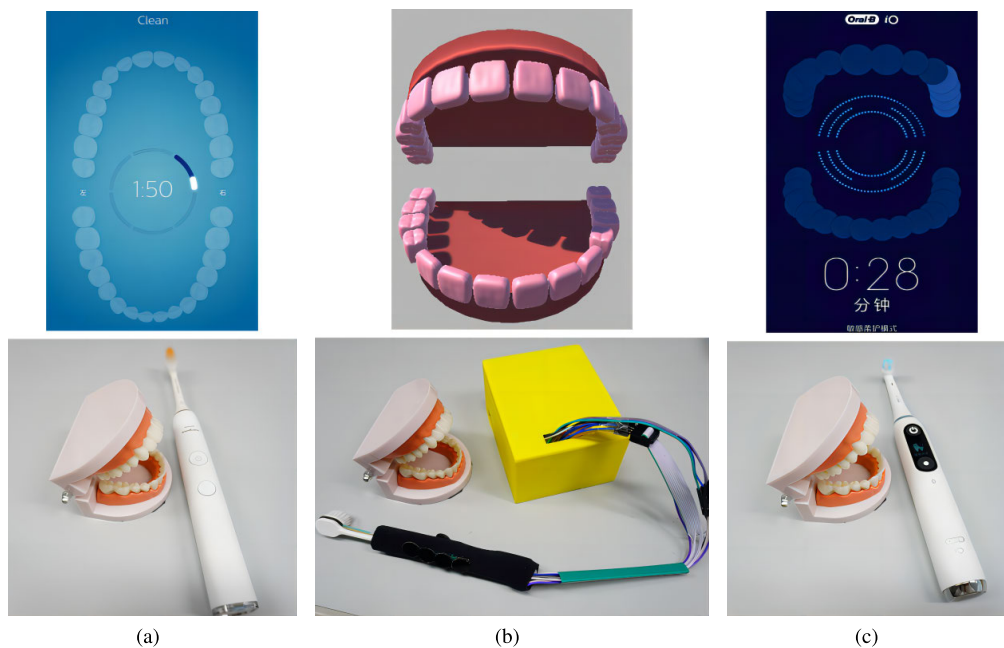
FIGURE 29. Three groups of toothbrushing system. (a) is a Philips electric toothbrush with its User Interface; (b) is the 3D brushing monitoring system of this research with the User Interface designed by Unity; (c) is an Oral-B electric toothbrush with its User Interface.

TABLE 6. The order in which participants did three groups of usability experiments.

Subjects	Gender	Age	Philips toothbrush	Oral-B toothbrush	3D brushing monitoring system
Subject A	F	28	1	2	3
Subject B	M	24	1	3	2
Subject C	M	27	2	1	3
Subject D	F	24	2	3	1
Subject E	M	25	3	1	2
Subject F	F	23	3	2	1

of electric toothbrushes, tooth model, and corresponding APP(provided visual interface). Group B is the 3D brushing monitoring system designed in this research. As shown in Fig. 29, we simplified the experimental device.

In order to rule out the effects of the order in which different groups of experiments were performed. As illustrated in Table 6, we randomly arranged the participants to conduct three groups of experiments in different orders.

- 6 participants was invited to participate in this experiment.
- Participants simulated brushing activities on the tooth model using three corresponding devices.
- Brush each region evenly from 0 g to 300 g.
- Each region lasts about 10 seconds.
- Participant fills out the PSSUQ after completing each group experiment.

The PSSUQ is a 16-item standardized questionnaire. In this research, we used it to evaluate the usability of this 3D brushing monitoring system. Regarding the PSSUQ analysis, PSSUQ score starts with 1 (strongly agree) and ends with 7 (strongly disagree). The lower the score, the better the
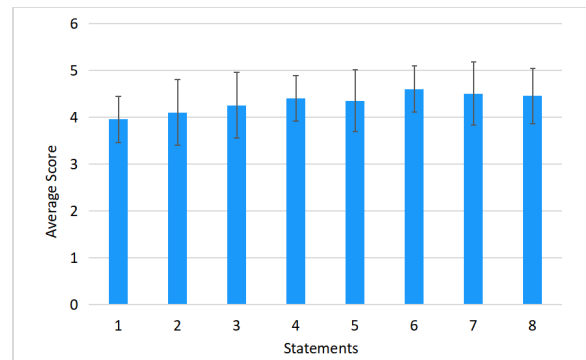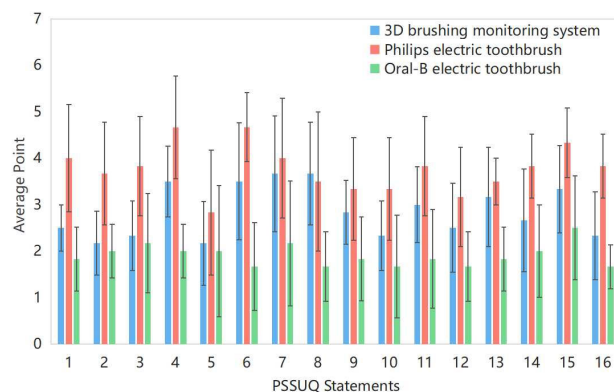

FIGURE 30. Average point and Standard Deviation of the six subjects for PSSUQ 16 statements of three toothbrushing system. Every statement starts with 1 (strongly agree) and ends with 7 (strongly disagree). The lower the score, the better the performance and satisfaction.

performance and satisfaction. As shown in Fig. 30, we calculated the average score and SD for each PSSUQ statement of three brushing systems among six subjects. It is evident that the Oral-B brushing system showed the best performance and satisfaction, followed by the 3D brushing monitoring system. The Philips brushing system had the worst performance and satisfaction among the three systems. However, the subjects also reported that the Unity-designed visualization interface was very intuitive and interesting, and it not only automatically adjusts the view to magnify details but also provides vivid brushing feedback.

We calculated scores for each sub-scale about 3 toothbrushing system.The overall score of PSSUQ reflects the overall usability of the system and is a composite score
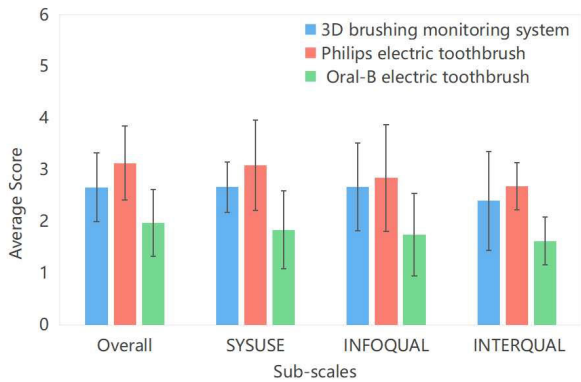
FIGURE 31. Average Score and Standard Deviation of the six subjects for each subscale of three toothbrushing system. Every statement starts with 1 (strongly agree) and ends with 7 (strongly disagree). The lower the score, the better the performance and satisfaction.

of all sub-scales including SYSUSE, INFOQUAL, and INTERQUAL. The SYSUSE score indicates the usability of the system, reflecting how easy it is for the user to use. The INFOQUAL score indicates the information quality of the system, reflecting how clear and understandable the information provided by the system is. The INTERQUAL score indicates the interaction quality of the system, reflecting how intuitive the interaction between the system and the user is. As shown in Fig. 31, the scores for the Oral-B brushing system are the lowest among the three systems, indicating that it is the easiest to use, has the simplest operation, has the best information quality and has the best interaction quality among brushing systems. On the other hand, the Philips brushing system is the worst in all aspects among the three systems. For the 3D brushing monitoring system, the scores between the sub-scales are also relatively similar. In comparison, this system is also an easy-to-use, simple to operate, complete in information and user-friendly system.

V. CONCLUSION

To better assess the effectiveness of brushing teeth, we proposed a low-cost smart system that is able to effectively track toothbrushing regions and detect the brushing force in real-time. We have systematically designed and experimented with each of the three main parts to ensure that each part can achieve its intended function. It not only can detect brushing region but also can detect brushing force. A 3D model user interface is designed to better visualize the detection results. We get some good results in this research. In addition, at present, there are few methods and researches on detecting toothbrushing force, and this method provides a new direction for detecting toothbrushing force.

For drawbacks, the system has limitations in terms of applicability, primarily due to Sampling Bias, as the samples are mainly concentrated on young individuals with no missing teeth. However, for people of different age groups and different tooth structures, the performance of this system may be affected. In order to enhance the system's applicability, in the future, we will consider expanding the sample size to

cover a broader range of age groups and tooth structures. Additionally, we will take into account more factors that may influence system performance, aiming to improve its generalization capability and accuracy.

In this study, our evaluation focused on the accuracy of brushing region and brushing force detection rather than the cleaning effect. The evaluation of brushing region and force detection was based on the appropriate application of force and comprehensive coverage of brushing areas, with each region brushed for a sufficient amount of time. We did not implement the cleaning effect feature in this study. However, in future work, we plan to collaborate with dental professionals to assess brushing effectiveness through various indicators after toothbrushing.

In clinical application, toothbrushing is highly correlated with oral hygiene and plaque removal. Therefore, we will also do more experiments and figure out other more effective methods to remove plaque and reduce the occurrence of gum disease. In addition, we will also improve the experimental model, such as using Bluetooth to implement the wireless transmission of data from the toothbrush device to the computer or smartphone to make the device more portable.

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