Do You Brush Your Teeth Properly? An Off-body Sensor-based Approach for Toothbrushing Monitoring

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***Abstract*—Oral hygiene is very important for a healthy life. Proper toothbrushing is one of the most important measures against dental problems. Poor toothbrushing methods can lead to tooth decay and other gum diseases. Unfortunately, many people do not brush their teeth properly and there is very limited technology available to assist them in compliance with the standard toothbrushing procedure. Sensor-based human activity recognition techniques have seen tremendous growth recently and are being used in various applications. In this work, we treat the compliance to the standard toothbrushing method as an activity recognition problem. We divide the toothbrushing activity into 16 sub-activities and use a machine learning model to recognize those activities. We introduce an off-body sensing solution that uses a detachable Inertial Measurement Unit (IMU), attached to the handle of the brush. The sensor captures the movements of the brush while reaching different parts of the teeth. Then a machine learning pipeline is trained to predict the brushing of different parts of the teeth. We evaluated the performance of the proposed approach in real-world scenarios and performed experiments with 10 different users. We collected our own data set and compared our approach with the wearable-based approach. The results show that our approach performs better than wearable-based approaches and can recognize the toothbrushing activities with 97.15% accuracy. We also evaluated our model for different types of brushes (manual and electric) and the results show that the proposed approach can work independently from the brush types.**

***Index Terms*—Toothbrushing, Activity recognition, IMU, e-Health**

I. Introduction

According to the Australia's Adult Oral Health Tracker report [5], released by the Australian Dental Association, oral diseases are among the most common diseases faced by the Australian people. Statistics show that 32.1% of individuals age 15 or above have tooth decay which is untreated and this ratio has increased by 6.6% since 2004. In 2016/17 alone, 10.2 billion Australian Dollars were spent on dental services in Australia. One of the main reasons for tooth decay is the disposition of bacteria over the tooth surface. This bacteria causes dental plaque which is a complex organic structure and is the root cause of the tooth decay and other gum diseases [41]. Toothbrushing is one of the most important measures against oral diseases (especially dental problems) [26]. Proper toothbrushing is very important for reducing plaque and other dental problems. The American Dental Association (ADA) recommends to brush the teeth twice a day for two minutes using the Bass technique [34]. But compliance to the proper toothbrushing technique is a major issue and various studies suggest that many people brush their teeth incorrectly without following the standard procedure [40, 11]. There is very limited technology to assess the compliance of toothbrushing at home. Even though electric toothbrushes are available in the market nowadays, the problem is not solved completely as it still relies on the users to move their hands properly to reach all the surfaces of the teeth. Most of these toothbrushes cannot detect the compliance to proper toothbrushing techniques in terms of duration and coverage. Therefore, there is a need for technology-based solutions to monitor the toothbrushing.

Ubiquitous sensing has emerged as a new field of research to solve the different problems in health care [38]. Nowadays, different sensors are used to monitor human activities such as sleeping [14, 1], medication taking [3], and many other daily activities [15], helping care givers and health professionals to provide better services to people. These sensing systems use various sensors to provide prominent results in various applications. Now, the question is whether existing techniques can be applied to toothbrushing monitoring? We tried to answer this question by looking into the related literature but there are three main challenges. Firstly, toothbrushing is very different from normal activities such as sleeping, walking, and cooking. The changes in the sensor readings caused by these normal activities are very significant and can be easily captured by the sensors. For toothbrushing, the changes caused are very subtle and the same techniques cannot detect the activity with high accuracy. Secondly, many of the wearable devices are custom-designed having different embedded sensors and battery which have high cost. But in the case of toothbrushing, having a high cost device is not feasible because the toothbrush

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needs to be changed frequently (e.g., after every three months). Thirdly, the related literature shows that many studies have tried to provide the solution for monitoring toothbrushing activity. However, there is a need for improvement as this area is relatively new and still lacks a cost-effective, energy-efficient and highly accurate solution.

In this paper, we propose an Inertial Measurement Unit (IMU) based solution for monitoring the toothbrushing activity. We use a detachable IMU unit, which can be attached and re-attached to different toothbrushes, thus making it re-usable after changing the toothbrushes. Acceleration and gyroscope data are transferred to an edge computing device which can be a smart phone or a laptop via Bluetooth. Hence, all the processing will be done on the edge device. More specifically, the raw sensor data is cleaned to remove any noise. The cleaned data is then passed through device variation removal phase in which a filter is applied to remove any variation caused by the differences of brush types. Once the data is cleaned, features are extracted to train the machine learning model for recognition of the brushing activity. The proposed system can be used by users in daily life to keep track of their toothbrushing style and can also be used by the dentists to analyse the toothbrushing style of the users. To the best of our knowledge, this is the first detachable, off-body sensor-based solution for detection of toothbrushing activity. Our proposed system is cost-efficient and easy to use. The major contributions of our work are as follows:

- We treat the compliance to the standard toothbrushing technique as activity recognition problem and classify the brushing activity into 16 sub-activities (corresponding to the 16 teeth surfaces). We employ several machine learning classifiers, and show that our system is able to correctly recognize these sub-activities.
- We exploit sensor fusion technique to generate pitch and roll features which improved the classification accuracy. We use both manual and electric toothbrushes and compare the accuracy of models trained with each, as well as a model trained with a mix of activities using both brush types.
- We evaluate our system in real world scenarios and perform experiments with 10 different subjects. We compare our proposed approach with wearable-based approach. Our approach can recognize the toothbrushing activities with $> 97\%$ accuracy, which is higher than the the wearable-based approach accuracy.

The remainder of the paper is organized as follows. Section II presents the related work in the area of toothbrushing monitoring using sensory systems. Section III presents our insight into designing a toothbrushing monitoring system. An overview of our proposed system is given in Section IV. The evaluation setup and experimental results are presented in Section V. Finally, we conclude our work in Section VI.

II. Related Work

Due to the importance of oral and dental health, toothbrushing monitoring and analysis has gained significant attention from the research community in recent years. From the related literature, one can find different approaches to monitor and analyze the toothbrushing activity. These approaches include vision-based, wearable-based, and modified brush-based solutions. Some techniques use motion capture systems and cameras to monitor and analyze the toothbrushing [9, 18, 20, 35]. Besides other issues such as complexity of processing, privacy is the main concern with these types of solutions. The most common approach found in the literature is to use IMU sensors for tracking the trajectory of brush movements for analyzing and monitoring the toothbrushing activity. These sensors can be used as wearable (wrist-worn) or by embedding them into the toothbrush (smart/modified brush). With recent advancements in the sensor technology, there has been a shift towards the use of these sensors as wearables (e.g., smart watch), objects of daily use, and mobile devices.

Wearable devices have been used in various areas of human activity recognition such as smoking [27], exercising [7], and daily life activities [28]. Huang and Lin [13] proposed a wrist watch based solution for monitoring toothbrushing, using inertial sensors embedded in a smart watch including accelerometer, gyroscope, gravity sensor, magnetic sensor, and microphone. The smart watch transfers the data to a tablet via Bluetooth which then uploads the data to the cloud for storing and processing. This technique also modifies the toothbrush by attaching a small magnet to capture the orientation of the toothbrush. This work uses the sensory data from the inertial sensors to recognize the brushing gestures which are modeled based on the basic motion such as wrist flexion, elbow flexion, shoulder flexion, and forearm rotation. The system also uses the acoustic data from the microphone to find the stroke frequency of toothbrushing. The proposed system uses Hidden Markov Model (HMM) to detect the order of toothbrushing surfaces. Another technique presented by Luo et al. [29] also uses the wrist-worn sensors for toothbrushing monitoring. This technique, called Hygiea, uses accelerometer, gyroscope and compass embedded in a smart watch to recognize toothbrushing activity. The proposed system uses Attention based Long Short-Term Memory (AT-LSTM) model [39] to achieve high accuracy for recognition of toothbrushing activity. To extend the battery life and reduce the power usage, this work uses Partially Observable Markov Decision Process (POMDP) [23]. One of the major challenges in using the wearable-based approaches for toothbrushing monitoring is that the activity is very different from other daily life activities. There are very subtle changes occurring in the sensors reading during the toothbrushing and these changes can be easily affected by other movements (e.g., hand movements).

Some solutions use acoustic signals for toothbrushing monitoring. For example, Korpela et al. [22] used audio signals received through a smartphone to monitor the brushing activity. This work uses HMM to recognize different phases of the brushing activity such as brushing the inner or the outer surface of the teeth and then scores each phase using a regression model. This approach requires the users to brush their teeth in the vicinity of a smart phone.

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Another widely used approach is to modify a toothbrush by embedding different sensors inside the brush and use the data from these sensors for monitoring the brushing activity. The concept of a smart toothbrush was first presented by Lee et al. [24]. In their study, they developed a custom-designed toothbrush by incorporating different sensors inside the body of the toothbrush. This work studies the relationship between the direction of the brush and the style of toothbrushing. Another similar technique was presented in [25] which uses an accelerometer and magnetic sensor embedded in the toothbrush to detect toothbrushing regions. The system was capable of identifying different brushing regions but was not able to recognize the compliance of the brushing activity to the standard procedure. Kim et al. [21] proposed a technique which also uses sensors embedded in the toothbrush. The proposed system collects the data from accelerometer and magnetic sensors embedded in the toothbrush and then applies a real-time three dimensional display to visualize the brushing activity of the subject.

A major issue with modified brush-based solutions is the cost. Since toothbrushes need to be changed very often (every three months), embedding different hardware components inside the toothbrush would be very expensive. Therefore, in this work, we present a detachable device-based solution which is cost-effective and can monitor the toothbrushing activity. We attach a device with multiple sensors to the handle of the toothbrush to capture the brushing activities. We use the sensor data to recognize the activity of toothbrushing. This device can be detached and attached again to another brush, thus reducing the cost.

III. Background

In this section, we present an overview of the advantages of our proposed system. The background of the Bass Toothbrushing technique, is also discussed.

A. Design Consideration

In this section we first describe the motivations behind our proposed approach.

Non-Invasive. Some solutions use cameras and motion capturing systems to monitor the toothbrushing activity which can cause privacy concerns. Other solutions require the users to have their smart phones with them to capture the audio signals. These approaches make the monitoring of brushing activity very difficult. In this work, we use a light-weight detachable device which can be attached to any toothbrush and can transfer the data to an edge device using Bluetooth.

Cost-Effective. An important factor in any system is the cost. Many solutions are proposed which use modified toothbrushes but they are expensive. Also, the toothbrush needs to be changed frequently which further increases the cost. Our solution is cost-effective as the same device can be attached to different brushes. If the users need to change the brush, all they need to do is to attach the device to their new brushes.

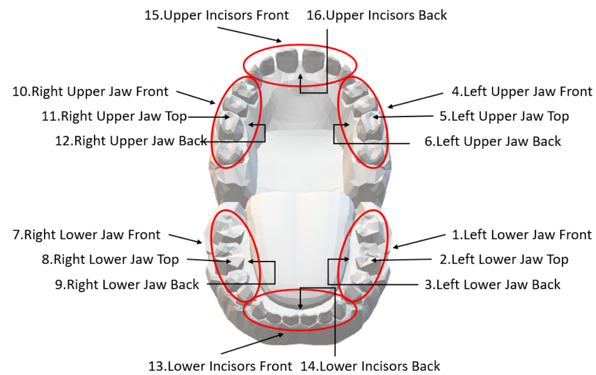

Fig. 1: Toothbrushing regions based on the Bass technique.

TABLE I: Sub-activities in toothbrushing.

1. Left Lower Jaw Front (LLJF)	9. Right Lower Jaw Back (RLJB)
2. Left Lower Jaw Top (LLJT)	10. Right Upper Jaw Front (RUJF)
3. Left Lower Jaw Back (LLJB)	11. Right Upper Jaw Top (RUJT)
4. Left Upper Jaw Front (LUJF)	12. Right Upper Jaw Back (RUJB)
5. Left Upper Jaw Top (LUJT)	13. Lower Incisors Front (LIF)
6. Left Upper Jaw Back (LUJB)	14. Lower Incisors Back (LIB)
7. Right Lower Jaw Front (RLJF)	15. Upper Incisors Front (UIF)
8. Right Lower Jaw Top (RLJT)	16. Upper Incisors Back (UIB)

B. Bass Toothbrushing Technique

There are four types of teeth in human mouth which are incisors, canines, premolars and molars. We divide these in 6 regions named as Left Lower Jaw (LLJ), Left Upper Jaw (LUJ), Right Lower Jaw (RLJ), Right Upper Jaw (RUJ), Lower Incisor (LI) and Upper Incisors (UI). There are three surfaces (front, top and back) which need to be brushed for LLJ, LUJ, RLJ and RUJ while 2 surfaces (front and back) for LI and UI. These are 16 possible regions [13] as shown in Figure 1 that we need to brush using the Bass technique recommended by the ADA [34].

Based on this, we classify the toothbrushing activity into 16 sub-activities given in Table I. Sufficient time is also a key factor for good toothbrushing results. It is recommended that the users should brush their teeth for two minutes twice a day [12]. However, only the time cannot guarantee the good practice of toothbrushing as there might be some regions which are left from brushing [13]. Many people spend more time on some regions while leaving behind the other regions. Proper toothbrushing means that a user has to brush all these regions and spend enough time on each of these regions to have good results. In our work, we monitor the position of the brush and the time spent in each position to recognize whether each region has been properly brushed.

IV. Proposed System

In this section, we describe our approach that includes a sensor-attached toothbrush and an activity recognition system that can classify different toothbrushing activities.

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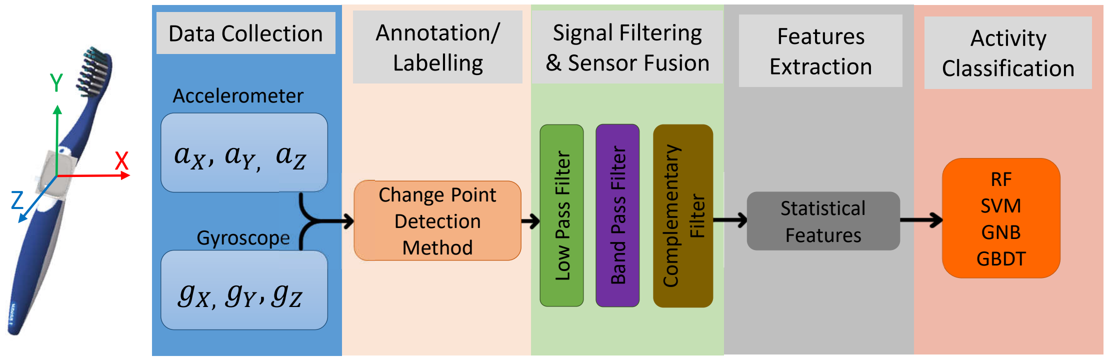

Fig. 2: Architecture of the proposed system.

A. System Overview

The architecture of the proposed system is given in Figure 2, and the main components of our system are as follows:

- *Brush-Attached Device*: The system consists of a small device attached to the handle of a toothbrush which can capture the motion of the brush while the user is brushing her teeth using the Base technique. The data captured by the attached device is passed on to an edge device (smartphone or laptop) via Bluetooth for processing.
- *Annotation*: After transferring to an edge device, the data is labelled for training of the model. A basic annotation method is developed which can label the different regions in the toothbrushing using the ground truth.
- *Filtering and Fusion*: The data is then cleaned and the variation caused by different brush types is eliminated by passing the data through the filtering stage. Different filters such as low-pass, high-pass, and band-pass filters with different cutoff frequencies are applied in the filtering stage. The cleaned data from the accelerometer and gyroscope is fused by using a complementary filter.
- *Feature Extraction*: Different statistical features are extracted from the data in the feature extraction phase.
- *Classification*: Finally, the classification module recognizes the different regions of the toothbrushing using machine learning models.

B. Hardware and Data Collection

We use an inexpensive IMU called MetaMotionR (MMR) [30], shown in Figure 3. MMR is a very light weight (0.2 oz) and small device (27x27x4 mm) which can be used as wearable and can also be attached to any object. It has multiple sensors such as accelerometer, gyroscope, magnetometer, ambient light, barometer, and temperature sensor. MMR can easily be attached to any toothbrush handle (both electric and manual) and the data of selected sensors can be logged or streamed to a nearby device via Bluetooth. We use only accelerometer and gyroscope sensors in our work as these sensors can capture sufficient information (orientation of the brush head, region, etc) to recognize the activity of toothbrushing.

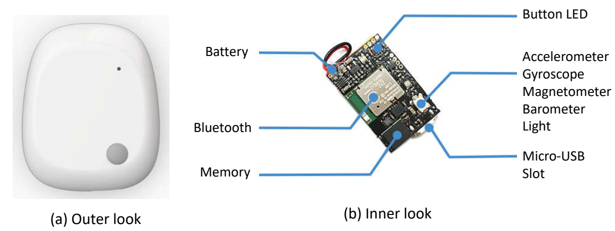

Fig. 3: MMR sensor.

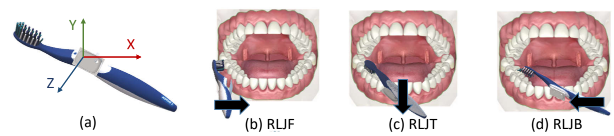

Fig. 4: Orientation of the brush while brushing different regions.

The accelerometer and gyroscope sensors measure acceleration and angular velocity relative to the earth gravitational field vector. For this reason they are insensitive to rotation around the vertical axis. As a consequence, provided the brush is held horizontally—the predominant orientation during toothbrushing—the measured accelerations and angular velocities do not change when users face different directions. As the user brushes different regions of the mouth, the roll and pitch angles will change. The different orientation of the toothbrush (MMR) are shown in Figure 4 while brushing the three surfaces of the RLJ. As can be seen from the figure, the x-component of the sensor's (accelerometer) reading will change with brush strokes (horizontal) while the y and z-components will change when changing the orientation of the brush for moving to different regions of the teeth.

C. Annotation

All the experiments were conducted in a real environment and the participants brushed their teeth in their natural manner. Each experiment was controlled to ensure that the subject

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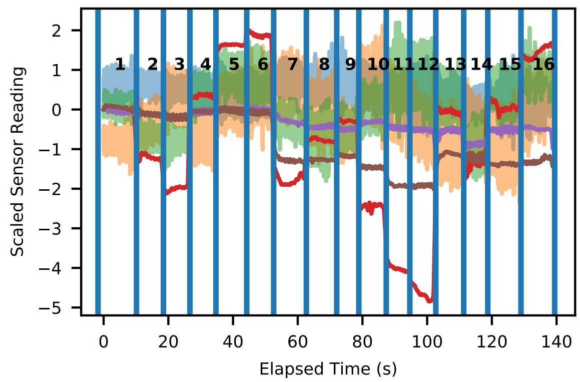


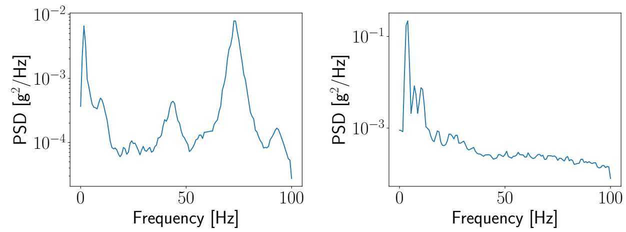
Fig. 5: Annotation of the 16 regions showing the raw sensor data with changepoints between activities indicated by vertical lines and class labels indicating the corresponding activity number (1-16).

followed the pre-determined sequence of activities to get the ground truth for training purposes. The only instructions given to the participants were about the sequence of the regions to be brushed i.e., which region to be brushed first and which one next (for labelling purposes). The experiments were also observed by the researcher (the lead author) to get the ground truth.

After the experiments, each session was manually annotated. The accelerometer's x,y and z-components exhibit consistent patterns due to the periodic brush strokes with changepoints between each activity—these become more visible when plotted with alpha transparency. The gyroscope measures angular velocity and by integrating the x,y and z-components, we can add the brush orientation (pitch, roll and heading) which show distinct levels during each activity with a step change between. Using changepoint analysis on the integrated gyroscope roll angle, we can accurately identify most of the activities [37] as shown in Figure 5. The changepoints between each activity (labelled 1 to 16 with the labels corresponding to the activities from Table I) are indicated by vertical lines. The accelerometer x,y and z-components render as shaded regions and the integrated gyroscope x,y and z-components render as near horizontal lines providing a high degree of visual separation between the activities.

D. Data Pre-Processing

In order to make sure that our model is robust enough to work for any type of toothbrushes, we used a mix of both manual and electric toothbrushes in our experiments. We used five different models of manual toothbrushes and three different models of electric toothbrushes (Oral-B Pro 800, Oral-B Pro 100, and Oral-B Vitality). The type and design of the toothbrush has a significant impact on the data captured by the attached sensor. When using a manual brush, the changes in the data are caused only by the movements of the brush to reach different regions of the teeth. Electric toothbrushes have a motor which causes vibration thus inducing noise to the signal captured by the sensors. In the case of electric brushes, the changes will be caused not only by the brush movements but also by the vibration of the electric brush. These changes need to be removed from the captured data before the data can be used for recognition, thus making the data independent of the brush model.



(a) Electric (b) Manual

Fig. 6: Power spectral density (PSD).

Figure 6 shows the power spectral density (PSD) of the accelerometer data captured for both manual and electric brushes. In the human activity frequency range of 0-20 Hz [4] both Figures 6a and 6b exhibit similar peaks in power spectrum. The 0 Hz peak represents the mean of the signal and the peak in the 0-20 Hz band is due to the brushing motion, generally around 4 Hz. Above 20 Hz there are significant differences between the two brush types due to the vibrations from the mechanical components of the electric toothbrush. We used a low-pass butterworth filter with a 2 Hz cutoff frequency to extract the 0 Hz component and a band-pass butterworth filter with a 2-6Hz frequency pass-band to extract the brush motion and eliminate the higher frequencies unrelated to the brushing action.

Finally a 6-DOF complimentary filter was used to fuse the accelerometer and gyroscope data to provide an estimate of the roll and pitch angles. A complimentary filter consists of two input stages, an *integrator* to estimate the roll and pitch from the gyroscope θ_g and a *coordinate transformer* to compute the roll and pitch angle from the accelerometer θ_a. The former exhibits drift whilst the latter exhibits noise. The drift is removed using a high-pass filter and the noise using a low-pass filter. The equation for the two filters is:

$$\theta = \beta * \theta_g + (1 - \beta) * \theta_a, \tag{1}$$

where θ_a is computed from the linear acceleration after applying zero-g offset [19] and coordinate transformation [32], θ_g is computed by integration of the gyroscope velocity and β is between 0 and 1, typically between 0.95-0.98. Figure 7 shows the block diagram of the filtering stage. The entire brushing session is passed through this stage before being passed to the feature extraction stage.

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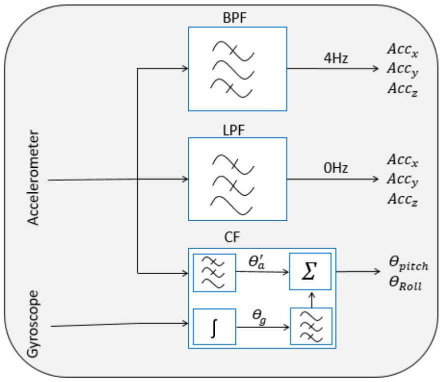

Fig. 7: Output of the filters.

E. Feature Extraction

Each session consists of 16 sub-activities and typically takes two minutes to complete. Each sub-activity is performed in sequence and not repeated. There is a short transition between sub-activities which is excluded. The sub-activities are extracted from each session and a rolling window is applied to each one. The window consists of two parameters, the length L in samples and the overlap O which has a range from 0% (subsequent windows do not overlap at all) to 100% (exclusive). There are $C = 8$ input features per window {'$Acc_{x,4Hz}$', '$Acc_{y,4Hz}$', '$Acc_{z,4Hz}$', '$Acc_{x,0Hz}$', '$Acc_{y,0Hz}$', '$Acc_{z,0Hz}$', 'θ_{pitch}', 'θ_{roll}'} resulting in a $\mathbb{R}^{L\times C}$ matrix X_{raw}. This matrix is reduced to a vector by applying feature extraction functions of the form $\Phi_i = f_i(X_{raw})$ where f_i is a function which maps from $\mathbb{R}^{L\times C}$ to $\mathbb{R}^C$ and then all the individual feature vectors are concatenated to produce the final feature vector $x = [\Phi_i, \Phi_{i+1}, \ldots, \Phi_n]$.

Feature extraction covers statistical, temporal and spectral domains. We experimented with feature importance to rank which specific feature extraction algorithms produces a measurable improvement in the model accuracy. We used TSFEL [6], a Python library for time-series feature extraction. We observed that the statistical features produced the highest accuracy. We selected mean, standard deviation, skewness, kurtosis, minimum and maximum, resulting in a feature vector of size 48. The features that had the highest impact on accuracy were mean, minimum and maximum, in particular when applied to the roll axis. This is most likely because the roll angle provides information on which surface is being brushed. The next most import features were the mean of the low-pass filtered accelerometer sensor and then the mean, minimum and maximum of the pitch angle. Pitch correlates well with upper *vs.* lower jaw.

We also investigated the spectral features, but only a single fundamental frequency was identified. We found that the fundamental frequency did not change significantly with activity; but, the peak power of the fundamental changed with brushing intensity and some users exhibited different intensity by activity—however this was not consistent. In addition, the standard deviation is correlated with the peak power of the fundamental frequency.

F. Classification Models

We used Random Forest (RF) [8] as our classification model as it has shown a good performance compared to other classifiers. Our pipeline was implemented in Python using Scikit-learn [33]. The model was trained to output class labels (1-16) given a feature vector derived from a time series window as described in Section IV-E. Given a sliding window over a toothbrushing session, the classifier will produce an isolated classification for each window indicating which region is most likely being brushed during the window.

V. Experiments and Discussion

A. Setup

In this section, we first describe the hardware used in our experiments followed by the setup of the different experiments.

We collected our data set under controlled conditions in five different locations (washrooms). As per the dentists' recommendations, toothbrushing should be done for at least two minutes. We attached the MMR device to the handle of the brush as shown in Figure 4 (a). We also used one MMR device as wearable (watch) worn by the participants on their brushing hand during the experiments. The purpose of the wearable device is to compare our approach with the wearable-based approach as used by previous studies [13, 29]. We recruited 10 healthy volunteers (5 females and 5 males). All the participants were aged 25-40 and having healthy teeth and gums. The main reason for this age group was the convenience as we can easily find the participants of this age group at our university.

Before the experiments, all the participants were given instructions about proper toothbrushing and the sequence (which side to start from and which side to next etc.) to follow for labelling purposes. Three participants (1 female and 2 males) used electric brushes while the rest used manual brushes of different types. The participants also wore a watch (having the other MMR device) on their brushing hand during the experiment. A researcher (the lead author here) was observing the experiment to get the ground truth. All the experiments lasted for about 2 minutes and the sampling rate was set to 200 Hz for both accelerometer and gyroscope sensors. The participants repeated the experiment (on next day) and a minimum of 2 and a maximum of 5 sessions were recorded for each participant. In total, we recorded 46 toothbrushing sessions. According to all the participants, there was no noticeable impact of the device attached to the brush. After each experiment, the data were transferred from both devices (attached and wearable) to an edge device (a smartphone or a laptop) via Bluetooth for further processing. For further details regarding the dataset, interested readers are encouraged to read [16, 17].

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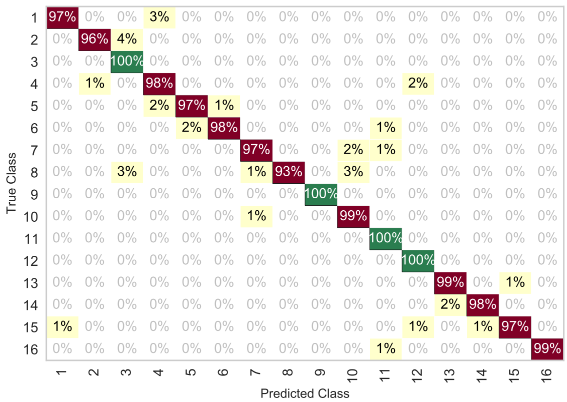

Fig. 8: Confusion matrix of toothbrushing activities classification using RF.

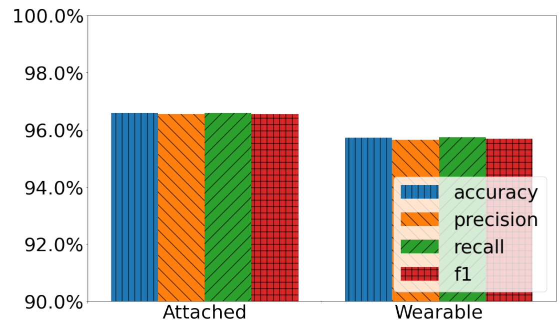

Fig. 9: Impact of the sensor location.

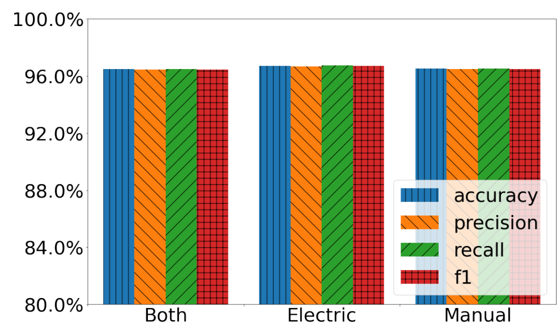

Fig. 10: Impact of the toothbrush type.

B. Results

In this section we present the performance of our system in identifying the activities outlined in Table I. Unless otherwise mentioned, we used 5-fold cross validation with RF as our classification algorithm. We used accuracy, precision, recall and F1 score as metrics for the performance evaluation of our model. Accuracy is the percentage of correct predictions over all the samples. Precision is the number of times the models makes the right prediction while recall can be defined as the number of times the model correctly recognizes the different regions of the teeth. F1 score can be calculated from precision and recall values. We further evaluated the performance of our approach with respect to training data set size, brush-attached *vs* wearable sensor, window size, brush type, and sampling rate. Finally, we compared RF with other classifiers including GBDT, SVM, and GNB.

1) Recognition Performance of the Proposed Model: The confusion matrix in Figure 8 shows how often the model misclassifies one activity for another. Values on the diagonal show how often the correct decision is made. As can be seen from the figure, the model can accurately recognize many activities with 100% accuracy. For some activities such as LLJT and RLJT, the classification accuracy is lower than the average. The reason behind this is that many users tend to keep the brush orientation almost similar while brushing certain regions. Similarly, some of the labels from LLJT are classified as LLJB while some of the labels from RLJT are classified as LLJB and RUJF. These issues can be overcome by increasing the size of the training dataset. The overall accuracy of the model shows that it can clearly recognize all the 16 sub-activities in the toothbrushing.

2) Wearable Sensor vs Brush-attached Sensor: Some of the previous studies in the literature used the wearable-based solution for toothbrushing activity recognition [13, 29]. We compared our approach with wearable approaches under the same conditions. As mentioned in Section V-A, we used one MMR device as wearable which was worn by all the users on their brushing hand during the experiments. We collected a separate data set from this wearable sensor. We applied the same pipeline steps on both data sets (one from brush-attached sensor and other from wearable sensor) and the results are given in Figure 9. As can be seen from the figure, we achieved higher accuracy for the brush-attached approach as compared to the wearable-based approach. The reason is that the attached sensor can better capture the brush movements as compared to the sensor wore on the wrist, thus better representing the different regions during the teeth-brushing.

3) Impact of the Toothbrush Type: In real life, people use different types of manual and electric toothbrushes. To evaluate the performance of our proposed model, we performed experiments with three data sets; 1) data from manual toothbrush, 2) data from electric toothbrush, and 3) data from both. The results are shown in Figure 10. One can see that the proposed model achieved almost similar accuracy for all three data sets which shows that the proposed model can accurately recognize the toothbrushing activity irrespective of the brush type.

4) Impact of Filtering: To show the impact of filtering, we conducted experiments with different models of electric and manual toothbrushes using unfiltered accelerometer data. The

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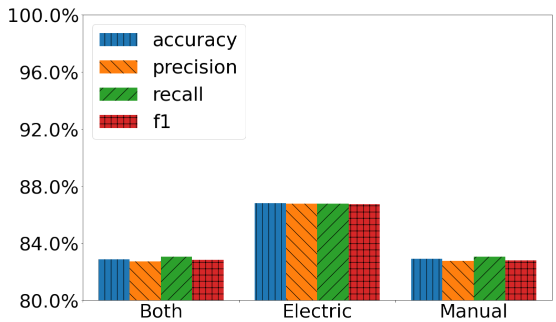

Fig. 11: Impact of filtering.

results of this experiment are shown in Figure 11. These results show that the electric toothbrush has higher accuracy using raw data only. This may be explained by less variation in the way test subjects brush using an electric brush. A manual brush can be used in different ways, for example the brush strokes can be along the direction of the teeth, or in a swirling pattern. Adding additional features such as pitch and yaw, and filters benefits manual brushing more.

5) Impact of Individual Sensor: Our data set includes data from the accelerometer and gyroscope sensors. However, another question we want to investigate is which sensor is most influential in recognizing the brushing activities. To this end, we extracted the accelerometer only data and built a new data set for our investigation. We studied the performance of our methodology for accelerometer only *vs.* the fused data approach. When only the accelerometer was considered the accuracy is 89.6%. When the pitch and roll angles from the complimentary filter were included, the accuracy increased to 97.1%. This shows that the angle of the brush is being held at has a considerable impact on the accuracy of the classification.

6) Impact of the Sampling Rate and Window Size: Selecting a suitable window size is important for feature selection. In this experiment, we evaluated the effect of the window size on the recognition accuracy of our system. The window size was varied from 50 samples (0.25 seconds) to 200 samples (1 second). The accuracy decreased as the window size was increased, as shown in Figure 12.

Sensor data sampling rate directly impacts the system lifetime [2]. However, capturing data with low-sampling rates may impact the classification accuracy. To inspect the effect of different measurement rate, we down-sampled the data sampling to simulate data collected at 100Hz, 50Hz, and 25Hz measurement rate, respectively. The same pipeline was applied to these new data sets. The results are shown in Figure 13. As can be seen from the figure, the model retained its high accuracy even when the sampling rate is halved i.e., at 100HZ, the accuracy is still 96.6%. This experiment shows that we can save the power of the sensor by reducing the sampling rate without compromising on the performance of the model.

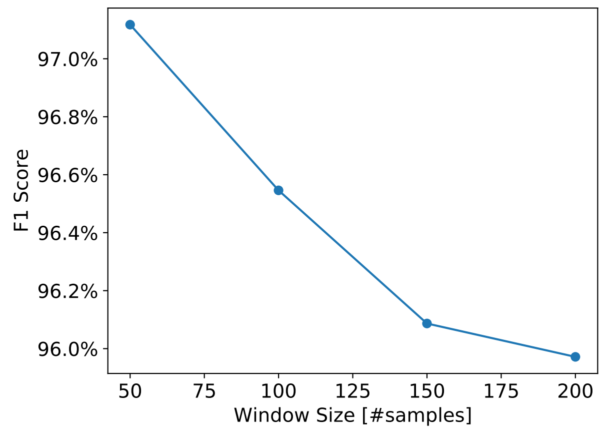

Fig. 12: Impact of the window size.

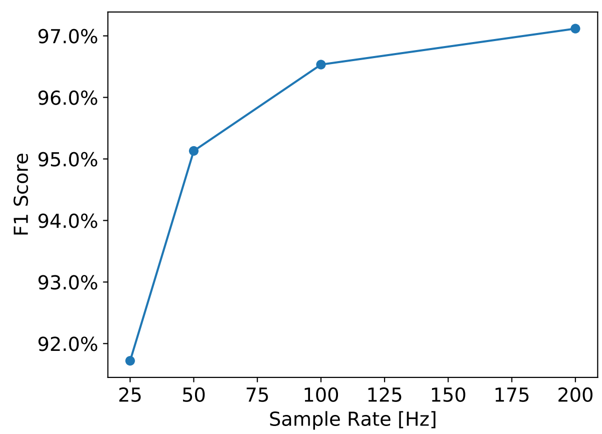

Fig. 13: Impact of the sampling rate.

7) Performance of Various Classifiers: We used different machine learning models to evaluate their performance for classification of toothbrushing activities. We compared the performance of RF with other classification models—including Support Vector Machine (SVM) [31], Gradient Boosted Decision Tree (GBDT) [10], and Gaussian Naïve Bayes (GNB) [36]. The parameters of each classifier were fine tuned to achieve the best accuracy. The results are shown in Table II. As can be seen from the results, RF achieved the highest accuracy as compared to the other classifiers, and therefore we selected RF as our classification model for all the experiments.

TABLE II: Comparison of different classifiers.

Model	Accuracy	Precision	Recall	F1 Score
SVM	88.98%	88.92%	88.92%	88.89%
RF	97.15%	97.12%	97.13%	97.12%
GNB	59.67%	60.00%	60.71%	59.36%
GBDT	96.86%	96.85%	96.84%	96.84%

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VI. Conclusion

In this work, we proposed an off-body detachable sensor-based solution for recognizing the toothbrushing activity. We used a low-cost IMU (Inertial Measurement Unit) attached to the handle of a brush (which can be detached and attached multiple times). The attached device captures the movements and orientations of the brush when a user moves the brush to reach the different regions of the teeth. The data is transferred to an edge device via Bluetooth for further processing. The data is cleaned and any noise or variation caused by the difference in the brush type is removed by applying a series of various filters. Each session is manually annotated to assign labels to different regions of the teeth.

We treated the compliance to the standard toothbrushing technique as activity recognition problem and classified the brushing activity into 16 sub-activities (corresponding to the 16 teeth surfaces as per the dentists recommendations). We tested basic classification models such RF, SVM, GBDT and GNB and selected RF in our proposed approach as it provided the highest accuracy compared to others. We evaluated the performance of our model in real world scenarios and conducted experiments with 10 volunteers at 5 different locations. We compared the performance of the proposed approach with the wearable-based approach. The results showed that our solution performed better than the wearable-based solution. We also conducted various experiments to investigate the impacts of various factors such as brush type, classification model, single sensor *vs* fusion, and the sampling rate. In all our experiments, we found that the proposed model is robust and can provide high accuracy for any type of brushes and can retain its performance for different sampling rates.

Looking forward, we plan to increase the size of our data sets, the number of participants, and include other sensor data as well. We will also look into other interesting insights from the data and explore additional factors involved in the toothbrushing such as right-handed *vs* left handed, gender, and age. Exploiting deep learning techniques is one main direction for our future work.

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