# LumiO: A Plaque-aware Toothbrush

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# ABSTRACT

Toothbrushing plays an important role in daily dental plaque removal for preventive dentistry. Prior work has investigated improvements on toothbrushing with sensing technologies. But existing toothbrushing support focuses mostly on estimating brushing coverage. Users thus only have indirect information about how well their toothbrushing removes dental plaque. We present LumiO, a toothbrush that offers users continuous feedback on the amount of plaque on teeth. Lumio uses a well-known method for plaque detection, called Quantitative Light-induced Fluorescence (QLF). QLF exploits a red fluorescence property that bacterium in the plaque demonstrates when a blue-violet ray is cast. Blue-violet light excites this fluorescence property, and a camera with an optical filter can capture plaque in pink. We incorporate this technology into an electric toothbrush to achieve improvements in performance on plaque removal in daily dental care. This paper first discusses related work in sensing for oral activities and interaction as well as dental care with technologies. We then describe the principles of QLF, the hardware design of LumiO, and our vision-based plaque detection method. Our evaluations show that the vision-based plaque detection method with three machine learning techniques can achieve F-measures of 0.68 - 0.92 under user-dependent training. Qualitative evidence also suggests that study participants were able to have improved awareness of plaque and build confidence on their toothbrushing.

#### **ACM Classification Keywords**

H.5.2. Information interfaces and presentation (e.g., HCI): User interfaces; I.4.9. Image processing and computer vision: Applications

### **Author Keywords**

Toothbrush; plaque detection; quantitative light-induced fluorescence; oral care; healthcare application.

# INTRODUCTION

Maintaining a healthy oral environment is important to prevent cavities and periodontal diseases. Dental plaque is a colorless

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(or often pale-yellow-colored) biofilm that grows on teeth and along gum lines. It contributes to many oral diseases including the two above, and daily removal of plaque is critical to their prevention. Toothbrushing is an effective daily dental care method to remove plaque if it is performed properly. However, it is difficult for users to know how successfully they have removed plaque as they brushed their teeth without help of special dental care products or checks by a professional dentist.

This problem stems from the fact that users do not necessarily have direct feedback on the status of plaque removal while toothbrushing. There exist several ways to check the existence of plaque available for daily toothbrushing at home. Plaque disclosing products (e.g., tablets and solutions) are perhaps the most common and inexpensive approach. They stain plaque in deep red or blue to make it more visually identifiable. However, it can be demanding to use these products every time before toothbrushing. Users also have to use a mouth mirror to identify plaque at the inner part of the mouth (e.g., molars). This is not desirable because users may have to check repeatedly during toothbrushing.



Figure 1: LumiO, a plaque-aware toothbrush. (a) The LumiO toothbrush. (b) An example intraoral image LumiO captures. The sensing component consists of blue-violet light LEDs and a camera with an optical filter to excite the QLF property. The pink reflection indicates the locations of plaque. (c) A vision-based plaque detection result using SVM. The red points represent areas recognized as plaque.

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Bacteria in plaque has a fluorescent property, known as Quantitative Light-induced Fluorescence (QLF) [3, 4, 16]. In QLF, blue-violet light causes red or pink reflection by bacteria. There exist QLF-enabled intraoral cameras for non-professional use. However, they are not yet commodity devices in general families despite their affordable cost (roughly 100 - 150 USD as of March 2016). Unfortunately, these devices suffer from the same issue as plaque disclosing products and mouth mirrors. Users would have to switch a brush and camera back and forth until they remove plaque successfully. This switching is not only a burden for many users, but also make feedback about plaque removal discontinuous. We consider that this discontinuous feedback cycle is a key problem to be solved.

To provide continuous feedback on removal of plaque during toothbrushing, we create LumiO, an electric toothbrush that embeds a blue-violet light intraoral camera in its head (Figure 1a). LumiO continuously monitors plaque by using QLF. The LumiO camera system captures intraoral images, and performs a vision-based algorithm to identify how much plaque covers the teeth that users are currently brushing (Figure 1b and 1c). The system then provides users with feedback about whether they have brushed well or not by changing the intensity of the toothbrush head vibration. When users successfully remove plaque, the device weakens vibration, and they will be encouraged to brush other parts of the teeth.

This work examines the feasibility of integration of a toothbrush and OLF-enabled intraoral camera for providing improved awareness on plaque removal in daily dental care. More specifically, it offers three following contributions:

- The hardware design of a plaque-aware toothbrush: Our work presents the integration of a QLF-enabled camera component into a head of an electric toothbrush. Our hardware implementation does not include special production process, and is ready for scaling.
- The implementation of a vision-based plaque detection method: We develop a vision-based approach to identifying plaque in intraoral images taken by the LumiO device. It detects the amount of plaque while toothbrushing with LumiO, and provides feedback to users.
- **System and user evaluations of LumiO**: To validate our design of LumiO, we conducted a small-scale evaluation. The results confirm the feasibility and benefits of a plaque-aware toothbrush.

In this paper, we first discuss prior work on sensing for oral activities and interaction, commercially-available oral care technologies, and related literature on toothbrushing support. We then explain the principles of QLF and its limitations. We present the hardware design and vision-based plaque detection method of LumiO. We report our small-scale laboratory evaluation for validating the design of LumiO, and discuss possible improvement for future work.

# **RELATED WORK**

# Oral Activity and Interaction Sensing

Oral activities are involved in various human actions, such as eating, speaking, and breathing. Thus, systems can infer user's context, intention, or their activity status by oral sensing. Amft et al. [1] used the combination of a surface electromyography (EMG) and a microphone placed on a user's neck to detect swallowing activities for dietary tracking. Their sensor was able to distinguish swallowing dry and wet food at approximately 85% accuracy. Yatani and Truong created BodyScope [18] to track internal sound from the throat with a microphone attached to a user's neck. In user-dependent training, their sensor was able to classify twelve different activities at an accuracy of 79.5% Rahman et al. further improved the hardware design of a wearable acoustic sensor and demonstrated more robustness than BodyScope [13].

Some sensors are designed to be placed directly inside the user's mouth. Kim et al. developed an intraoral sensor to detect bruxism [5]. They embedded a pressure sensor in a bite guard, and confirmed its feasibility. Li et al. created a small sensing component with an accelerometer that can be embedded in a tooth [10]. Their evaluation revealed that a user-dependent SVM classifier achieved an F-measure of 93.8% in recognizing oral activities. But their results also showed that the accuracy decreased to 59.8% under user-independent training

Prior work has also exploited the intraoral space for creating novel interaction. Saponas et al. demonstrated the feasibility of utilizing the movements of a user's tongue for interaction by using a custom-made orthodontic dental retainer equipped with optical sensors [14]. Slyper et al. created a tongue joystick with which an actor inside can control her articulated head costume [15]. These projects suggest potentials of intraoral sensing for designing new forms of interaction.

The research above suggests the richness of the field in intraoral activity recognition and interaction design. Our work differs from the prior work discussed in this section because this work focuses on an oral care application.

# Commercially-available Oral Care Technologies

Smart toothbrushes (toothbrushes with sensing technologies) recently become commercially available. For example, Braun is going to sell a smart toothbrush<sup>1</sup> that equips a pressure-sensitive brush head as well as a position and orientation sensor on the holding part. Users can pair the toothbrush with their smartphone via Bluetooth. The smartphone then uses front cameras to perform video recognition to determine which part of teeth users are brushing. It also display users' brushing performance on the screeen. Brushing too hard can hurt teeth, and applying right pressure is a key for successful toothbrushing. The sensors in this toothbrush also monitor the level of pressure users are applying. The power toothbrush stops vibration when pressure becomes too intense.

Other commercially-available toothbrushes offer mobile game apps to encourage children's toothbrushing. Examples include

<sup>&</sup>lt;sup>1</sup>Braun, the Oral-B Genius http://oralb.com/en-us/genius

Kolibree<sup>2</sup>, Beam<sup>3</sup>, and PlayBrush<sup>4</sup>. These devices are self-contained or an attachment to ordinary toothbrushes. Their sensing capability is mostly limited to motions, and differs from this work.

Intraoral scanners are used in the dental clinics or hospitals to construct a 3D model of the patients' teeth and diagnose oral cavities. Most of these scanners comprise a camera and a depth sensor [11]. Such sensors might provide unique values for daily dental care, but they do not directly measure plaque on teeth, which is our primary goal to achieve.

Qscan<sup>5</sup> is a mobile device that utilizes the QLF property. The device has a yellow-filtered window at its center and casts blue-violet light. Although this device is easy to use, users are able to only see plaque at front teeth (i.e., incisors and canines). Gum lines along with molars are also locations where plaque tends to be developed, and additional support is still necessary.

## **Toothbrushing Support**

There are several projects related to applications with interactive toothbrushes in the context of ubiquitous computing and Human-Computer Interaction. We categorize them into two research focuses: toothbrushing coverage estimation and toothbrushing education.

Toothbrushing coverage estimation means assessing what portion of the teeth users have brushed and how well. Lee et al. [8, 9] added an accelerometer and a magnetic sensor to a toothbrush. Their device recognizes its position and orientation to estimate the location where the user is brushing. Their study confirmed that such enhanced toothbrushes can potentially support professionals for educating patients' daily dental care. Korpela et al. [6] used toothbrushing sounds to estimate brushing coverage. A smartphone placed next to the sink records audio signals, and performs hidden Markov models (HHMs) to detect where users are brushing. They divided the mouth into four regions: the inner surface of front teeth (FI), the outer surface of front teeth" (FO), the inner surface of back teeth (BI), and the outer surface of back teeth (BO). They also defined rough and fine brushing strokes: "rough" indicates that a stroke is too forceful while "fine" represents smaller, lighter brushing. By combining the regions and stroke types, they defined seven classes (including a not-brushing status but excluding FI-Rough and BI-Rough due to an insufficient amount of data). Their classification results achieved an accuracy of 78.3 %. Their study also showed that the accuracy varied drastically by various factors, such as the distance between participants and the smartphone.

Dentists recommend different practices on toothbrushing though they are not well shared among general user populations. Thus, toothbrushing education is one of the dentists' increasing interests, and there have been several research projects to support this. Lee et al.'s work also aimed at providing support for toothbrushing education [8, 9]. The

<sup>4</sup>http://www.playbrush.com/en/

<sup>5</sup>http://www.qraydental.com/qlf-producten/qscan/ overzicht-qscan



Figure 2: The Miharu-kun device, a commercially-available intraoral camera with QLF functionality. (a) A view of the front. (b) A zoomed view of the camera part (RGB mode). (c) A captured intraoral image in the RGB mode. (d) A zoomed view of the camera part (QLF mode). (e) A captured intraoral image in the QLF mode. The pink portions are plaque (manually annotated with white arrows).

system visualizes the position and orientation of a toothbrush in a virtual 3D space by using smart toothbrushes developed by themselves. Chang et al. [2] created an educational system to motivate kindergarten children to toothbrush by introducing a gamification concept. The system has an external camera capturing kids' toothbrushing to assess their performance. It also includes a monitor displaying a cartoon of teeth filled with dirt. As kids toothbrush sufficiently well, cartoon dirt disappears, and clean white teeth appear.

As seen above, existing research on toothbrushing performance assessment mostly relies on coverage estimation. Sufficient brushing coverage and duration can be associated with good plaque removal [7]. However, brushing coverage does not offer direct information about plaque removal. We hypothesize that users would gain more solid confidence on their toothbrushing by having such feedback. To this end, we determine to investigate the design of a plaque-aware toothbrush and its viability.

## QUANTITATIVE LIGHT-INDUCED FLUORESCENCE

LumiO exploits Quantitative Light-induced Fluorescence (QLF) in its hardware design. QLF utilizes the natural fluorescence of teeth to discriminate between caries and sound enamel [16]. The caries lesion spots have weaker fluorescence radiance than that of surrounding sound enamel areas. QLF uses light in a wavelength around 405 nm (which is blue-violet) to excite yellow-green fluorescence in a range above 520 nm. Thus, an intraoral camera with a yellow high-pass filter ( $\lambda > 520$  nm) captures sound enamel in green.

<sup>&</sup>lt;sup>2</sup>https://www.kolibree.com/en/

<sup>&</sup>lt;sup>3</sup>https://www.beam.dental/tech



Figure 3: The LumiO hardware construction. (a) The LumiO device. (b) The camera used in the LumiO hardware. This component consists of the camera head and main board. (c) We modify the camera by attaching an optical high-pass filter to its lens and replace the lighting components with blue-violet LEDs. (d) We solder the camera directly onto FFCs and waterproof it with resin. (e) (From left to right) An intact Oral-B ProWhite brush head, a head with its hair removed, and only the brush part. (f) The toothbrush head with the camera board placed between two modified ProWhite brush head (viewed from the side). (g) The back of our modified Oral-B electric toothbrush. We solder wires on electrodes to control the power switch. (h) A zoomed view of the camera part. The camera is completely isolated from the brush, and stays still even when it is activated.

There are commercially-available intraoral cameras that have QLF functionality. Miharu-kun (RF Co., Ltd, Figure 2) is one example of those. Its camera has the resolution of  $640 \times 480$  pixels with the focal length of 10 - 20 mm. Figure 2c and 2e compares pictures taken with Miharu-kun in the normal RGB and QLF modes. The camera in the QLF mode captures the area of plaque although it is not a high-end sensor. We thus confirmed that the integration of cameras in these devices into a toothbrush can serve our purpose.

Clinic trials also confirm that QLF excites red autofluorescence by plaque [4]. Coulthwaite et al.'s study [3] found that this fluorescence attributes to certain species of bacteria in plaque. Heinrich et al. [4] suggested using QLF as an evaluation method for plaque removal. In QLF, an enamel, plaque, and gingival area brights green, red and brown, respectively. This spectral characteristic is beneficial in a vision-based classification method because it is straightforward to distinguish teeth and plaque. A common metric to quantify plaque on teeth in a vision-based approach is a Plaque Percent Index (PPI) [12]. It is defined as the number of red pixels divided by the total area of the teeth:

$$PPI = \frac{\text{\# of plaque (red) pixels}}{\text{\# of teeth (red and green) pixels}}$$
(1)

Our LumiO system uses a variant of this PPI to quantify plaque on teeth. We will explain this in detail later.

Although QLF is a promising technique, it has limitations for accurately measuring the amount of plaque. Van et al. [17] compared images taken under QLF with or without plaque disclosure. They revealed that only the portion of the plaque around the gingival margin and interproximal areas showed red fluorescence. Their study found that the disclosed area was approximately 62% larger than the red fluorescence region. They further concluded that a mature biofilm mainly causes the red autofluorescence. In other words, relatively young plaque on the tooth surface does not always show red fluorescence without disclosure. However, QLF without disclosure is still useful in detecting developed plaque and it can inform users of where they should brush carefully. We thus decided to investigate the feasibility of incorporating the QLF functionality into a toothbrush.

## LUMIO HARDWARE

Figure 3a shows our current LumiO hardware prototype. The LumiO hardware comprises a camera, toothbrush head, electric toothbrush body, and a microcomputer. We explain each component in detail.

#### **Intraoral Camera**

An intraoral camera is the main sensor in LumiO, and has to satisfy the following requirements:

- Small enough to be integratable into a toothbrush head,
- Short focal length, and
- Low-cost for production.

Figure 3b shows the camera device (GDT MZ-USB001 Endoscope) we use in the current LumiO prototype, and Table 1 describes its specifications. As shown in Figure 3b, the camera consists of two boards: the main and camera parts. The main board has integrated circuits to convert the signals from the camera, and it connects to an external computer through USB. The camera board has a CMOS sensor covered

Resolution	640x480
Color depth	24 bits
Focal length	2 - 10 cm (best at 6 cm)
Angle of view	60°
Frame rate	10 fps
Operating voltage	5V
Power	120 mA / 30µW
Cost	6.99 USD

Table 1: Specifications of the camera used in LumiO.

by a black plastic casing with an adjustable lens. Four white LEDs are placed around the camera.

We make two modifications on this camera for building the Lumio prototype. To retarget this camera for QLF, we replace the white LEDs with Bivar SM0603UV-400 which can emit blue-violet light in a wavelength of 405 nm. We also attach a sheet of an high-pass optical filter ( $\lambda > 520$  nm) to the top of the plastic casing over the lens.

We extend the connection between the main and camera board with 10 cm of flexible flat cables (FFC, Figure 3d). This allows for the separation of the main and camera board. We then waterproof these boards. We create a silicon mold to make a transparent, waterproof cover for the camera with resin. This cover protects the camera and LEDs while not occluding the light and vision (Figure 3d). We cover the main board and FFCs together with a heat-shrinking tube, and fill the gap between the tube and cables with hot glue.

# **Toothbrush head**

Our LumiO device embeds the camera in the center of the toothbrush head. We modify a Braun's Oral-B ProWhite to create the LumiO toothbrush head. The Oral-B ProWhite toothbrush head has brushes at the periphery and a small rubber component at the center, designed for holding toothpaste (Figure 3e, left). When the connected electric toothbrush body turns on its motor, the head rotates the bottom ellipse plate back and forth. Thus, if we simply attach the camera to this head, it will also vibrate, causing substantial blur in captured images.

To fix the camera, we combine two Oral-B ProWhite toothbrush head. We remove the rubber component in one toothbrush head in order to create a space for the camera (Figure 3e, center). We also modify another toothbrush head so that it only has the bottom ellipse plate. We attach the camera to the back of this toothbrush head, and cover it with the other head. We then place a supporting part to connect the two heads (Figure 3f). In this manner, the LumiO toothbrush head can still vibrate while the camera remains at the center.

Figure 4 presents an example image captured by LumiO. Figure 5 shows an example of intraoral images captured by LumiO and Miharu-kun. Due to its longer focal length, captured images by LumiO are less clear than Miharu-kun. However, as seen in this figure, LumiO captures pink reflection by plaque. Although we did not perform a quantitative comparison of captured intraoral images between LumiO and



Figure 4: An example image captured by the LumiO prototype. The regions reflecting in pink are plaque (manually annotated with white arrows).



Figure 5: A comparison of captured intraoral images between (a) LumiO and (b) Miharu-kun. Although the image brightness is different, LumiO captures pink reflection by plaque.

Miharu-kun, we concluded that the current LumiO prototype demonstrates a QLF capability sufficiently for our purpose.

#### Toothbrush body and plaque feedback mechanism

The current LumiO prototype uses Braun's Oral-B Electric Toothbrush Plaque Control DB4510NE for its body. DB4510NE has no special sensor or functionality, and users can switch on and off its vibration motor with a button on the surface. We solder wires on two electrodes connected to the switch (Figure 3g) to bypass to an Arduino Pro Mini. We use Pulse Width Modulation to control the facade of vibration strength of the toothbrush. After trials, we found that the minimum duty cycle to successfully activate the toothbrush head is 23%. The LumiO device vibrates at the highest intensity until the area of plaque in the captured image is below the pre-determined threshold. It otherwise activates the motor at the minimum duty cycle. In this way, the LumiO device can offer haptic feedback about plaque on the teeth users are currently brushing. We designed the feedback to be self-contained so that users would not need to have any additional device.

# **VISION-BASED PLAQUE DETECTION**

The LumiO system analyzes intraoral images from the camera and assesses the amount of plaque on teeth. The system uses this analysis result to determine the vibration strength. Thanks to QLF, a vision-based approach can easily identify plaque and enamel by their colors. We use different machine learning techniques (Naïve Bayes (NB), k-nearest neighbor (kNN), and Support Vector Machine(SVM)) for recognizing them, which we explain in a later section.

After identifying plaque and tooth regions, we calculate plaque coverage in a similar definition to PPI. Let  $A_p$  and  $A_e$  be the area of the plaque and enamel regions, respectively. Here, we define the teeth region as the sum of the plaque and enamel areas (i.e.,  $A_p + A_e$ ). We determine  $A_p$  and  $A_e$  by counting the number of pixels that are labeled as plaque and enamel, respectively. We calculate the plaque coverage *PC* as follows:

$$PC = \frac{A_p}{A_p + A_e} \tag{2}$$

The current LumiO system uses this *PC* metric to determine the intensity of toothbrush vibration. We use 0.01 as the threshold for switching the vibration intensity because plaque regions are quite visible in QLF intraoral images by human eyes. Future work should revisit this threshold after consultation with professional dentists.

In our current LumiO prototype, an external computer connected to the camera through USB runs the plaque detection process. Additional hardware improvements may enable mobile devices to perform the detection through wireless connections. If the recognition algorithm is lightweight (e.g., naïve color thresholding), we expect that plaque detection can even run on the device.

#### PLAQUE DETECTION METHOD COMPARISON

We conducted a small-scale evaluation on LumiO. We had two objectives in our evaluation: comparing different machine learning methods for plaque detection and uncovering user experience of Lumio. For these purposes, we conducted two experiments. In this section, we explain our first experiment, comparing plaque detection performance with three machine learning techniques.

Although we wanted to include more participants in our experiments, we decided to run in a very small scale. Our evaluation included tasks with using the LumiO device, and thus we needed to be very careful about hygiene. To this end, we provided a LumiO toothbrush head to each participant. This also, however, limited the number of participants we could recruit because we had to produce Lumio toothbrush heads by ourselves. Due to this limitation, we were only able to recruit four participants (two males and two females, the average age of 21.5; P1 - P4).

## Procedure

We first collected intraoral image data by LumiO. All of the participants regularly performed toothbrushing once or twice a day. One of them also used dental flosses or interdental



Figure 6: F1-scores against different k values (under the conditions of RGB, with-toothpaste and user-dependent training). F1-scores start saturated at k = 11.

brushes. But none took regular dental checks or treatments by professional dentists.

At the beginning of the study, we explained the study procedure and LumiO device. We disabled the vibration and plaque detection for this part of the study. Participants were then asked to capture intraoral images with LumiO. We instructed them to put the LumiO's head at different locations of teeth. They were asked to move the brush back and forth in gentle strokes as if they would perform toothbrushing with a normal electric toothbrush. We collected intraoral images under conditions of using toothpaste and not. We used Sunstar GUM Dentalpaste S-380<sup>6</sup> toothpaste (white-colored). Data collection always started with the condition of not using the toothpaste. Each participant was strictly instructed to use her own LumiO toothbrush head. We also performed sterilization to the LumiO body with alcohol disinfectant.

We extracted twelve frames that captured plaque areas from videos recorded by LumiO. Two raters, including one of the authors, manually labeled the area of plaque, teeth, and gums in each frame. We only used the areas both raters agreed as the positive examples for each category, and discarded the rest. We tested the RGB and HSV values of each pixel (thus, three values per pixel) as features in our classification. Each frame was 640 x 480 pixels, and as a result, we had 15.6M samples in total.

The number of samples is too large for the testing purpose, and we down-sampled to 40,000 samples for each class. Samples were equally taken from all participants. We used this down-sampled dataset for our testing. To avoid a potential bias by this down-sampling, we performed random sample selection ten times with different seeds, and created datasets. We report the average results of our testing with ten datasets.

We tested Naïve Bayes (NB), k-nearest neighbor (kNN), and Support Vector Machine (SVM) with the RBF kernel in our evaluation. We examined classifiers under

<sup>&</sup>lt;sup>6</sup>http://jp.sunstargum.com/lineup/pstcem/dentalpaste/

Feature		R		HSV				
Training	User-c	lependent	User-i	independent	User-	dependent	User-	independent
Toothpaste	With	Without	With	Without	With	Without	With	Without
NB	0.68	0.64	0.67	0.56	0.76	0.75	0.66	0.68
kNN	0.92	0.91	0.67	0.68	0.91	0.90	0.67	0.69
SVM	0.92	0.91	0.67	0.66	0.91	0.90	0.69	0.69

Table 2: Overall F1-measure results of the three machine learning techniques.

With toothpaste											
		Use	r-depend	lent	U			er-independent			
	Teeth	Plaque	Gum	Total	Recall	Teeth	Plaque	Gum	Total	Recall	
Teeth	38332	1214	404	39950	0.96	29402	6582	3966	39950	0.74	
Plaque	1093	36061	2827	39981	0.90	7253	21682	11046	39981	0.54	
Gum	842	3103	36123	40068	0.90	2149	8339	29581	40068	0.74	
Total	40268	40379	39354			38804	36602	44594			
Precision	0.95	0.89	0.92			0.76	0.59	0.66			
Without toothpaste											
Teeth	38235	1430	224	39889	0.96	26626	5790	7474	39889	0.67	
Plaque	1651	35255	3172	40078	0.88	6775	23776	9527	40078	0.59	
Gum	495	3888	35650	40033	0.89	3395	7402	29236	40033	0.73	
Total	40380	40573	39046			36795	36969	46236			
Precision	0.95	0.87	0.91			0.72	0.64	0.63			

Table 3: The confusion matrices for recognition results using SVM and the RGB features.

both user-dependent and independent training. In the user-dependent training, we performed 5-cross validation; therefore, we used 80% and 20% of the data for each participant to train and test a classifier, respectively. In the user-independent training, we used data from three participants for training and the rest for testing. Thus, we performed 4-cross validation for the user-independent training. We tested the *k* value from 1 to 29, and chose k = 11 as the performance became saturated (Figure 6). For determining hyperparameters in SVM, we used 2K samples of the training data. This portion of the data was not included for training the classifier.

## Results

Table 2 summarizes the results of our classification test. Our results show that kNN and SVM outperformed NB under the user-dependent training. But the three methods were comparable when trained under the user-independent training protocol. Training protocols affected the overall accuracy while the features (RGB vs. HSV) and the existence of toothpaste did not influence much.

Table 3 presents confusion matrices of SVM with the RGB features. This table again confirms small effects on the accuracy by toothpaste. It also shows that the precisions and recalls decrease for all classes in the user-independent training.

Figure 7 illustrates four examples of recognition results. These recognition results were under the user-dependent training. NB tended to under-estimate plaque regions. kNN and SVM were accurate, but sometimes caused mis-classification as seen in the second to fourth rows. In-depth analysis on mis-classification results may lead to further improvements though it is beyond the main scope of this work. Our quantitative results confirmed that plaque detection was possible at a reasonable accuracy.

# QUALITATIVE LABORATORY EVALUATION

We also conducted a small-scale qualitative evaluation to investigate the user experience of LumiO. The objective of this part of the evaluation was to confirm that LumiO can offer improved awareness of how well participants were able to remove plaque during their toothbrushing. Similar to the previous experiment, the number of the participants was limited, and quantitative metrics (e.g., usability scales or subjective workload indices) are not appropriate. We thus decided to take a qualitative method to examine user experience of LumiO.

## Procedure

We instructed participants to come to our laboratory again. We captured intraoral images before asking participants to brush teeth with LumiO. We used the Miharu-kun device for this video-capturing. Participants were then asked to perform



Figure 7: Examples of successful and unsuccessful plaque detection (under the user-dependent training). (From left to right) Raw images captured with LumiO; ground truth data; and recognition results with the three machine learning algorithms. Green, red and yellow represent teeth, plaque, and gums respectively. The first row shows a successful example where all classifiers recognized well. The second row is an example where the three classifiers showed different results. The third row shows an example of over-estimating plaque areas. The fourth row is another failure case where a large portion of teeth was recognized as gums.

toothbrushing with LumiO using toothpaste. We instructed them to toothbrush as long as they liked, but it was two minutes long at minimum. After completing the task, we had short semi-structured interviews to obtain quantitative feedback on LumiO. None of our participants was native or proficient in English. We thus interviewed in their native language and transcribed and translated quotes to English as faithfully as possible for the report in this paper.

We used kNN (k = 11) as the classifier because it was able to run in real time and its performance was comparable with SVM. We trained the classifier with data from all the participants obtained for the comparative evaluation. During the study, the system ran classification for each frame of 307K (640 × 480) pixels. This number was too large even for kNN to run in real-time. Therefore, we randomly sampled 3000 pixels with a  $5 \times 5$  elliptical kernel, followed by dilation. Figure 8 shows an example result.

Each participant completed one session which lasted approximately one hour. All participants were offered approximately 15 USD in a local currency as a compensation at the end of the study.

## Results

#### Improving Awareness of Plaque

All participants expressed positive experience of LumiO, particularly improved awareness of plaque on teeth. Two participants explicitly commented the benefit of LumiO we wanted to achieve.



Figure 8: An example result of the recognition process used for the qualitative evaluation. (a) A raw image captured by LumiO. (b) Recognition results of sampled pixels shown as colored dots. Green, red, and yellow represent teeth, plaque, and gums, respectively.

*I did not really know where my teeth have got dirty, and it is painless that the toothbrush automatically detects it.* [P1, female]

It is hard to see the inner part of the mouth even with a mirror. This [LumiO] gave me a feeling that I was successfully getting rid of plaque. [P2, female]

Another participant, P3, mentioned that LumiO can solve a common problem that people do not always know when they should finish toothbrushing.

*I usually stop toothbrushing when TV commercials end. But, I like it [LumiO] because I can know when I should finish my toothbrushing.* [P3, male]

P4 agreed on the benefits of LumiO for similar reasons, but he was not very sure about the feedback.

*I felt different vibration strength, but I could not tell how the device determined it.* [P4, male]

He suggested possible improvements about the feedback design. We will discuss them in the later section.

## Building Confidence on Toothbrushing

As LumiO offers feedback about plaque, participants were able to build confidence on their toothbrushing. This is another promising result for the LumiO design. P3 and P4 explicitly mentioned that the feedback by LumiO contributed to their confidence on toothbrushing.

Because I had perceivable feedback like vibration sounds, I felt that I was brushing well. [P3]

*I had some sort of assurance that (LumiO) was brushing well because the device detected plaque and feedbacked to me.* [P4]

### Possible Improvements on LumiO

The current LumiO device has a relatively large brush head. This made participants feel uncomfortable when they tried to brush the inner part of their mouths. Downsizing the head is critical to improve the viability of LumiO.

The brush head was too big. It was difficult to brush the inner part. It should be half the size. [P1]

Our participants were generally positive about the haptic feedback of LumiO, but P2 expressed some potential embarrassment caused by the vibration sound.

It was a bit embarrassing to me that the (vibration) sounds were large. People might think that my teeth are full of plaque. [P2]

To make LumiO more socially acceptable for use in a public space, she suggested another haptic modality channel.

It might be interesting to use heat as feedback. Because only I can feel that feedback. [P2]

P4 was the person who did not clearly understand the LumiO's feedback. He wanted to have clearer feedback about plaque, such as a numerical score.

I could not really know whether I had plaque or not through the feedback. I want to see numeric values as well as vibration strength. Maybe on a smartphone. [P4]

P3 suggested another improvement on the LumiO's feedback to indicate where he should brush next.

*It would be great if the device can guide me to where my teeth are dirty.* [P4]

## DISCUSSIONS

Our comparative evaluation on machine learning techniques for plaque detection revealed higher performance with kNN and SVM than NB. It also confirms that the classifiers performed well under the user-dependent training. We expected that they would achieve similar results even under the user-independent training. However, the accuracy results were lower in all conditions and techniques. In the worst case, there was a 0.25 score decrease in the F-measures between the two training protocols (classifier: SVM, feature: HSV, and no toothpaste). One possible explanation is that we did not perform adjustment of image properties across the participants (e.g., brightness). These properties can be subject to how widely the user opens her mouth as well as ambient light. This might have contributed to causing varied feature distributions, potentially resulting in lower accuracy.

Our results reveal that the effects by toothpaste were not large. Figure 9 shows an intraoral image when one of our participants was toothbrushing with toothpaste. As seen in this figure, when toothpaste is dissolved with water and saliva, it does not cover teeth and gums much. After users rinse their mouth at least once, the effects by the toothpaste are further decreased. We thus conclude that LumiO has a potential to be usable in real toothbrushing.

We also found that intraoral images were often too dark and difficult to identify plaque locations even in eye-balling. Adding more blue-violet LEDs in the brush head is one solution. Another possible approach is to replace brush hairs with optical fibers. Light can pass through them directly on the surface of teeth and gums. These fibers can also be used as a channel for image capturing. Thus, they can offer a much closer view of plaque and teeth, and a toothbrush with such



Figure 9: An intraoral image when a participant was toothbrushing with toothpaste. Plaque regions are manually annotated.

optical fibers may offer better detection results. Future work should consider these hardware modifications.

In our user evaluation, participants expressed positive values of LumiO even after a short period of use. In particular, qualitative results we obtained clearly indicate a strong potential to improve the awareness of plaque and contribute to developing confidence on toothbrushing. The results also suggests a number of improvements, encouraging further research in this space.

# LIMITATIONS

Although this work demonstrates the feasibility and potential benefits of LumiO, there are several limitations in the current prototype and evaluation. As explained in the section above, not all kinds of bacteria exhibit the QLF property. Thus, LumiO does not always guarantee the complete removal of plaque on teeth.

We do not claim that this work has confirmed medical benefits of LumiO in oral care. Study results need to be re-examined by professional dentists. Future work should also re-validate the labels in our dataset through devices approved for professional use or annotations by dentists. Nevertheless, our results encourage researchers to further examine medical implications of LumiO.

Our current plaque detection method runs in a pixel level. Although SVM generally performs well, its computational cost is relatively high and it does not run in real time in our current implementation. The primary objective of this work is to examine the feasibility of the LumiO concept, and therefore, we decided not to optimize our vision-based method rigorously. Future work should investigate more efficient image processing as well as better recognition methods. For example, clustering before executing classification may improve the recognition rates. Our evaluation only had a very limited number of participants. As stated, our hardware production and hygiene issues constrained the scale of the study. But the hardware design is ready for larger-scale production. Our contributions thus are not intrinsically limited in terms of technology scalability.

# CONCLUSION AND FUTURE WORK

Dental care is an important activity in personal health management. We present LumiO, a toothbrush that can detect plaque on teeth users are currently brushing. LumiO utilizes the QLF property to recognize how much plaque remains on teeth. We describe the hardware design of the current LumiO prototype and explain our vision-based plaque detection algorithm. Our evaluation confirms a potential of LumiO's viability. A quantitative performance comparison on different machine learning techniques shows that plaque detection was possible at a reasonable accuracy. Qualitative feedback from our participants supports our hypothesis that they were able to have improved awareness of plaque and build confidence on their toothbrushing.

Future work should expand the validation of LumiO to a larger scale. In our current LumiO prototype, we intentionally design feedback about plaque in a self-contained manner. But LumiO may be able to offer users richer information about brushing by using additional devices, such as smartphones and smartwatches. We will explore different interface design to further improve user experience of toothbrushing with novel sensing technologies.

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