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RESEARCH ARTICLE

Evaluation of Hand-Scaling Skills of Dental Hygienist Students: Identification of Contact Between Hand-Scaler Blade Tip and Tooth Surface

TOMOKO YUI¹, (Graduate Student Member, IEEE),
SUNG-GWI CHO^{1,2}, (Member, IEEE), YUKI SATO^{1,3}, YASUAKI ORITA¹,
MING DING⁴, (Member, IEEE), JUN TAKAMATSU⁵, (Member, IEEE),
TAKAHIRO WADA¹, (Member, IEEE), AND
TSUKASA OGASAWARA¹, (Life Member, IEEE)

¹Nara Institute of Science and Technology, Ikoma, Nara 630-0192, Japan

²Division of Electronic Engineering, School of Science and Engineering, Tokyo Denki University, Ishizaka, Hatoyama-machi, Hiki-gun, Saitama 350-0394, Japan

³Department of Computer and Information Sciences, Graduate School of Science and Engineering, Ibaraki University, Hitachi, Ibaraki 316-8511, Japan

⁴Institutes of Innovation for Future Society, Nagoya University, Furo-cho, Chikusa-ku, Nagoya 464-8601, Japan

⁵Microsoft Corporation, Redmond, WA 98052, USA

Corresponding author: Tomoko Yui (yui.tomoko.yn2@is.naist.jp)

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ABSTRACT Dental hygienist students require a self-learning simulator to learn the correctness of hand-scaling techniques. An essential technique in hand scaling is the maintenance of contact between the tip of the hand-scaler blade and the tooth. However, imaging-based methods cannot effectively reveal this contact because the gingiva and buccal mucosa conceal the blade. Therefore, this study aimed to propose a method to identify the appropriate contact state of the blade with the tooth by using an inertial measurement unit (IMU) attached to the hand scaler and a force sensor attached to the target tooth. The hand-scaling motion was measured in an experiment in which participants were instructed to use the tip or middle of the blade to contact the tooth. The contact state of the blade, whether it was the tip or the middle, was identified using 18 features, including the average and standard deviation of nine dimensions of force, acceleration, and angular velocity with a support vector machine (SVM). The results showed that the model using all 18 features could classify the contact state with an accuracy of 97.1%. Furthermore, the accuracy was 95.9% with the 12 features from IMU alone, which was not significantly different from the accuracy with 18 features. The accuracy was 88.8% with six features from the force sensor alone. These results indicate that the IMU alone can identify the correct contact state, highlighting the possibility of creating a realistic simulator for training dental hygienists in evaluating the blade-contact state.

INDEX TERMS Dental hygienist, hand scaling, motion measurement, inertial measurement unit, force sensor.

I. INTRODUCTION

A. BACKGROUND

Hand-scaling is the process of removing tartar and other dirt on tooth surfaces by mechanical manipulation using the tip

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of a hand-scaler blade (*hereafter referred to as tip*) [1]. It is one of the most important tasks for dental hygienists and is difficult to master because it requires precise tip operation by moving the hand scaler to remove the firmly adhered deposits on the tooth surface. An overview of the hand-scaling motion is presented below.

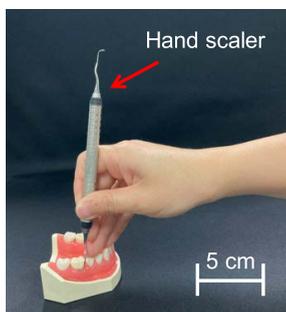


FIGURE 1. How to hold a hand scaler.

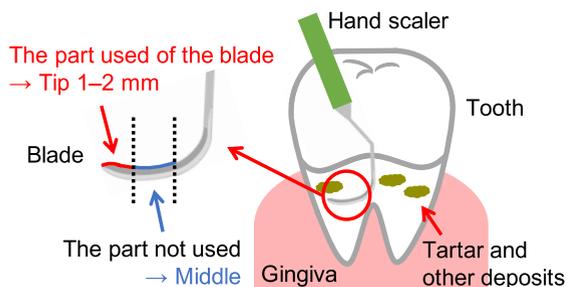


FIGURE 2. Correct use of the blade for hand scaling.

- The hand scaler is grasped like a writing instrument, as shown in Fig. 1. The ring finger of the hand holding the hand scaler is placed on an adjacent tooth and used as a fulcrum.
- A 1-2-mm tip of the hand-scaler blade is used, as shown in Fig. 2. The tip is kept in contact with the tooth surface, and up and down strokes of 2 to 3 mm are applied along the tooth surface, as shown in Fig. 3.
- Fig. 4 shows the motion of forearm rotation, which is the basic operation of the hand scaler. Forearm pronation and supination correspond to the motion used when lowering the blade to the stroke start position and when the blade is raised to the stroke end position, respectively. Stable and repetitive motions are ideal.

Dental hygienist training institutes spend considerable time on training dental hygienist students to acquire the correct hand-scaling technique. Through repetitive training using an oral cavity model, students practice this technique, which is difficult to master. Although one-on-one guidance is the most effective approach because some aspects of the technique are difficult to convey verbally, teachers may be unable to spare time to attend to all students' practices. Furthermore, oral cavity models have no function to automatically identify the correctness of hand scaling when students are self-learning. Without the ability to judge the correctness of their own techniques, students are unable to practice efficiently. Thus, while learning hand scaling, practice without constant feedback regarding the technique is inherently inefficient.

A simulator that also evaluates the student's skill can offer significant advantages for students to improve their technique. Simulation has been widely used in the education of medical professionals [2]. Simulation practice is

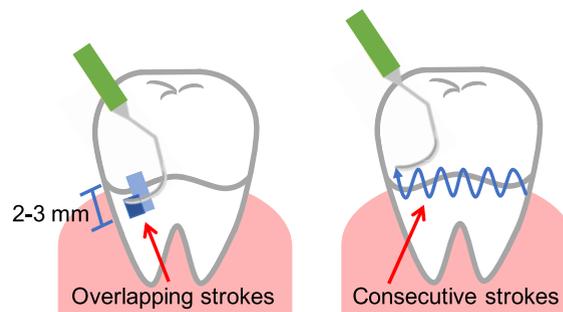
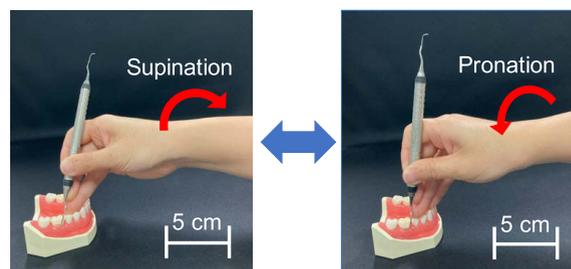


FIGURE 3. Stroke in hand scaling.



Stable repetitive motion is ideal

FIGURE 4. Hand-scaler operation: forearm rotation.

considered particularly important in the acquisition of surgical skills because it allows sufficient practice before students are allowed to treat patients [3], [4]. Consequently, students can learn from their mistakes without the fear of harming the patient [5]. Thus, simulation education can serve as an efficient and ethical method for training students to deliver safe medical care to patients [6], [7]. The scope of simulation training has been expanding and is now also being used to evaluate skills [8] because it allows detailed feedback and objective evaluation [9].

Therefore, we focused on a function implementable with an actual self-learning simulator that provides feedback on the correctness of student's hand-scaling motions and thereby improves their technique. Among the important aspects of the safety and efficiency of hand scaling, the use of the tip is particularly important, as shown in Fig. 2 [1]. The tip may damage gingiva when it moves away from the tooth surface [10], and therefore, the use of the middle of the hand-scaler blade (*hereafter referred to as middle*), as shown in Fig. 2, is incorrect and a typical example of a dangerous action performed by students. Teachers should guide students to use the tip instead of the middle when the blade is in contact with the tooth surface. However, beginner students experience difficulty in evaluating this point while focusing on other aspects of the technique. Thus, automatic evaluation and feedback on this aspect could greatly facilitate hand-scaling practice.

B. RELATED RESEARCH

Previous research has included training systems using virtual reality (VR) [11] and imaging technologies [12]. In research using VR technology, the purpose is to build a simulator for tooth scaling training using VR and evaluate its

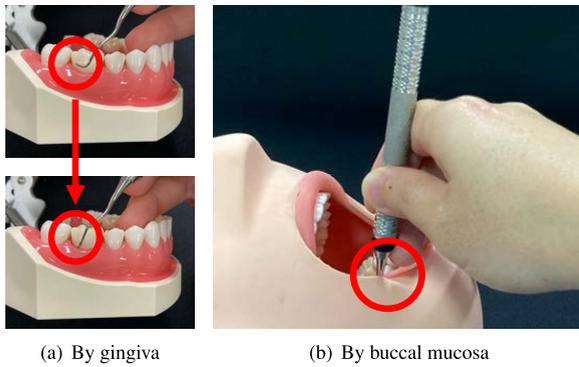


FIGURE 5. Example of a concealed hand-scaler blade.

training effect. Hand scaling can be performed on virtual intraoral teeth displayed on a head-mounted display (HMD). It includes a motion input part that imitates the handle of a hand scaler, allowing the practice of hand scaling motions. The HMD also displays the magnitude and direction of the force exerted by the tip of the hand scaler on the teeth, as well as the appropriate force magnitude and direction. Prior research examined the effects of training using this simulator based on the subjective evaluations of experienced participants and the number of successful cases of artificial tartar removal before and after training. Comparing the group using this simulator with the group that practiced removing the paint on a painted tooth model, which is the conventional practice method, showed that this simulator was more effective.

Research using imaging technology, the camera captures the hand-scaling motion using an AR marker attached to the rear end of the hand-scaler grip and a mannequin that simulates the head with the model of the oral cavity. The system estimates the motion of the tip from the image information of the AR marker attached to the rear end of the hand-scaler grip. A virtual hand scaler is displayed on top of the camera image of the mannequin. For example, the back teeth are concealed by the mannequin's cheek and not visible on the camera image. During hand scaling of the back teeth, the tip of the virtual hand scaler is to be displayed on the mannequin's cheek. Because the tip may be concealed by the gingiva and buccal mucosa during the operation, as shown in Fig. 5, a camera may not adequately visualize the contact or the absence of contact between the tip and the tooth surface.

C. LIMITATIONS OF EXISTING TECHNOLOGIES

The correct motion pattern is created relatively easily because haptic feedback from the hand scaler handle and visual information are uniquely determined. However, creating realistic and practical feedback for incorrect motion patterns is difficult because their motion patterns are myriad.

We considered the possibility of extending the camera-based system using imaging technology. In this approach, precise information on the hand scaler and oral cavity model would be required to identify the state of contact. Although such information can be obtained by acquiring the

shape in advance [13], [14] or by using 3D reconstruction from images [15], [16], both methods have limitations. Preparation is not realistic because the shapes of oral cavity models and blades often change from the pre-modeling shapes by wear and deformation caused by practice and aging. On the other hand, with 3D reconstruction methods, it is difficult to achieve the required accuracy. The precision of the 3D reconstruction is less practical (0.5 mm) [12]. Blind spots on cameras have also become a major problem in the implementation phase.

D. PURPOSE

Therefore, we considered the use of an inertial measurement unit (IMU) as an alternative approach for contact identification. IMUs have been widely used in skill assessment in the field of sports [17], [18], [19] as well as the medical field such as surgery [20]. IMUs can allow recognition and measurement of minute motion. We thought the use of an IMU would be promising for hand-scaling evaluation as well.

Thus, this study proposed a method to classify tip or middle contact based on hand-scaler motion and the force on the target tooth. We measured the motion using an IMU attached to the hand scaler and the force on the tooth by a force sensor attached to the target tooth. We focused on motion because we considered that the difference between the correct and incorrect techniques would be reflected in the motion. The force on the tooth surface was measured by a force sensor because hand-scaling force is known to relate to an important factor in the effectiveness of removing dirt [21], [22].

We asked students to perform hand scaling on a specific tooth to verify the identification of the contact state of the tip using the system. From the IMU attached to the hand scaler and the force sensor attached to the target tooth, we extracted the features of motions and force. The contact state was then classified using a support vector machine (SVM) based on these features. To implement functions with immediate feedback on a small, low-spec, single-board computer, we verified whether it is possible to reduce the number of features. Hand scaling involves several technical aspects. In the future, the simulator may be equipped with functions to determine them simultaneously. In the present study, we aimed to maximally reduce the processing involved in data measurement, feature calculation, SVM, and memory in this function. Therefore, to determine whether the sensor configuration could be simplified, we examined whether the accuracy achieved with both sensors could be maintained while using either sensor alone. We further examined the minimum number of features within one sensor that would maintain an accuracy similar to that obtained with the two-sensor configuration.

II. MATERIALS AND METHODS

A. HAND-SCALING SIMULATOR

The participants performed hand scaling using the simulator, as shown in Fig. 6 (a). The buccal mucosa was removed to observe the blade of the hand scaler during the experiment. The simulator was created based on our previous study [23].

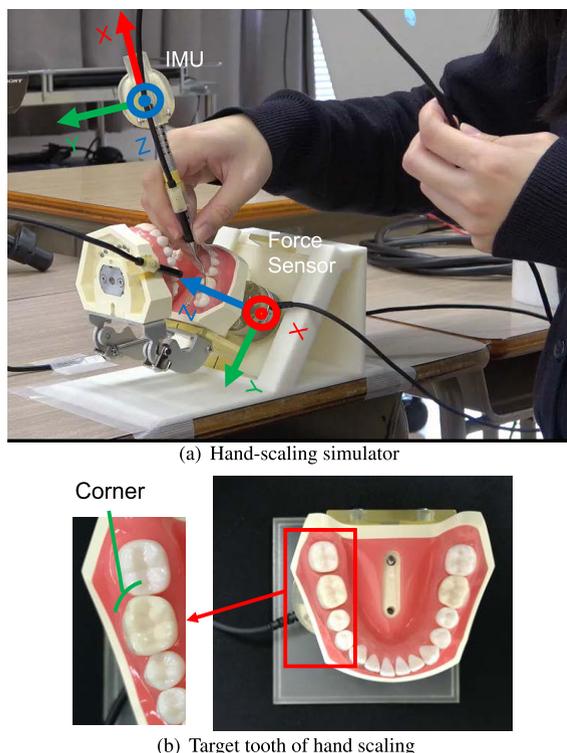


FIGURE 6. Experimental tool.

The hand-scaling motion was measured using an IMU (MetaMotion R; MbiientLab Inc.), and the force applied to the tooth was measured using a force/torque sensor (Mini40 SI-80-4; ATI Industrial Automation Inc.), as shown in Fig. 7. The IMU (Weight including case: 19.5 g) was attached to the end of the gripping portion of the hand scaler, as shown in Fig. 7 (a). The IMU can measure the motion of the hand scaler along three axes of acceleration and three axes of angular velocity. When the hand scaler was held upright and viewed from the tip, the Z-axis was vertical to the direction of the blade, vertical to the gripping portion, and pointing toward the right direction. Although the blade could not always be within the field of view, a camera (Endoscope Borescope Inspection Camera, KKmoon) was installed to capture images of the blade for reference in the analysis.

The force applied to the target tooth was measured using a force sensor that could evaluate force along three axes of force and three axes of torque, as shown in Fig. 7 (b). We used the data for the three axes of force in this study. A space was created between the target tooth and model frame to prevent contact between the target tooth (A2A-739-#46, Nissin Dental Products Inc.) and model frame. The force was transmitted to the sensor through the shaft. This was used to measure only the force transmitted from the hand scaler. The X-axis of the force sensor was in the buccal direction; the Y-axis was directed posteriorly from the target tooth; and the Z-axis was in the maxillary direction.

The hand scaler used was an original standard double-headed 13/14 #7 Gracie curette (Length: 17.0 cm, Weight: 21.0 g, Hu-Friedy Mfg. Co., LLC), which is commonly adopted in training schools. Each participant used a new hand

scaler to ensure uniform blade sharpness. The target tooth was also replaced with a new tooth for each measurement condition and each participant because the tooth surface was worn down by hand scaling.

B. PARTICIPANTS

The participants were students in the self-learning practice phase of hand scaling. We aimed to collect data from students' actual practice of hand scaling. Eighteen first-year students (18 females; age, 19.1 ± 0.8 years) from dental hygienist training schools in Japan participated in the experiment, including eight participants from Training School A, five from Training School B, and five from Training School C. One participant's data were excluded because it showed unusual characteristics for the force measurement values. This was caused by the fingernail touching the target tooth during hand scaling, because of which the contact force of the fingernail was also measured by the force sensor. This is an exceptional result, since the fingernails of people who perform hand scaling are usually not as long as hers. In the analysis, we used only the data measured from the other 17 participants. All participants had attended lectures on hand-scaling and received practical training at training schools before participating in the experiment. The textbook used was the same for each school, while the content of the lessons was unique and followed the guidelines of each school.

This study was approved by the Ethics Review Committee of Nara Institute of Science and Technology. All participants provided written informed consent before participating in the experiment.

C. HAND-SCALING TASK

The participants performed hand scaling on a specific tooth as shown in Fig. 6 (b) called the *lower right first molar* in the hand-scaling simulator shown in Fig. 6 (a). We asked them to perform the task based on the assumption that the tooth had buccal mucosa. They performed seven consecutive hand-scaling strokes as a single task. We asked them to perform basic operations such as holding the hand scaler, moving the blade on the tooth surface, and operating the hand scaler, as shown in Figs. 1, 2, 3, and 4 [1].

D. EXPERIMENTAL FACTORS

The experimental factor was the contact position of the blade, which was categorized as tip contact or middle contact, as shown in Fig. 8. Tip contact, wherein the tip is in contact with the tooth surface, indicated the correct technique. In middle contact, the tip is lifted off the tooth surface, which may damage the gingiva or other parts of the tooth. Thus, middle contact reflected an incorrect technique. Participants performed the hand-scaling task ten times for each of the tip and middle contacts.

E. SENSOR MEASUREMENT VALUES

Measurements were acquired from the IMU attached to the hand scaler and force sensor attached to the target tooth.

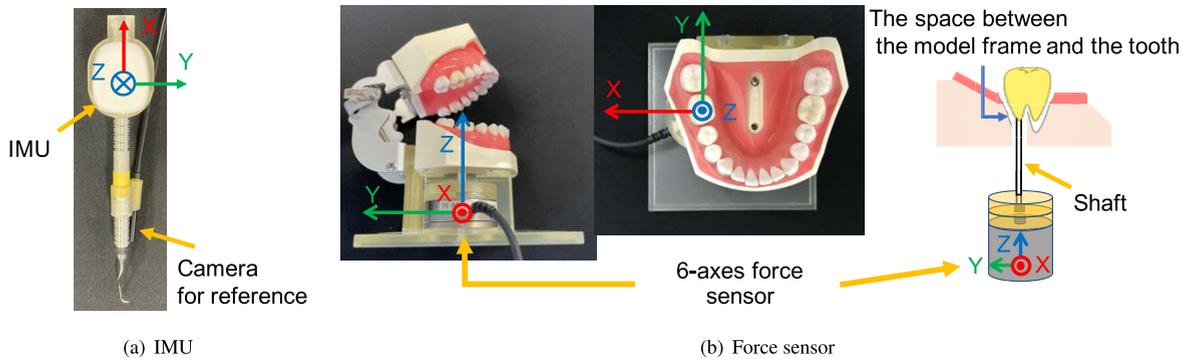


FIGURE 7. Sensor setting.

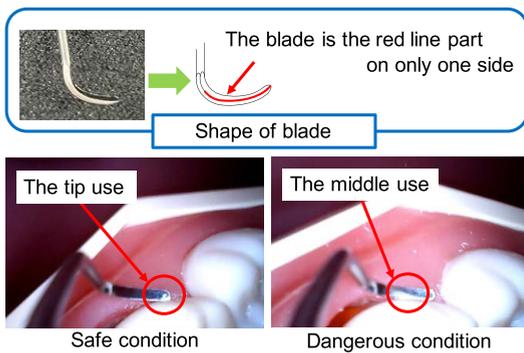


FIGURE 8. Contact between the blade and the tooth surface.

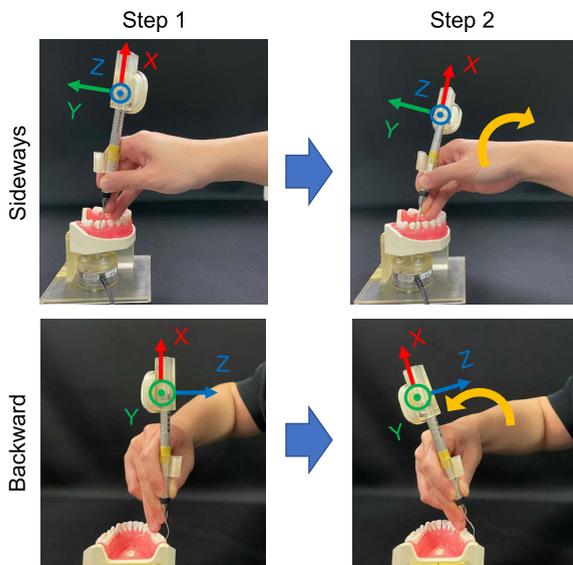


FIGURE 9. Three-axis of IMU during forearm rotation.

Measurements of acceleration, angular velocity, and force were acquired for each of the three axes (nine dimensions in total). Table 1 shows the correspondence of each axis in the forearm rotation motion (Fig. 9).

F. ANALYSIS METHOD

1) PREPROCESSING

The force, acceleration, and angular velocity data were synchronized using synchronous signals of the trigger motion,

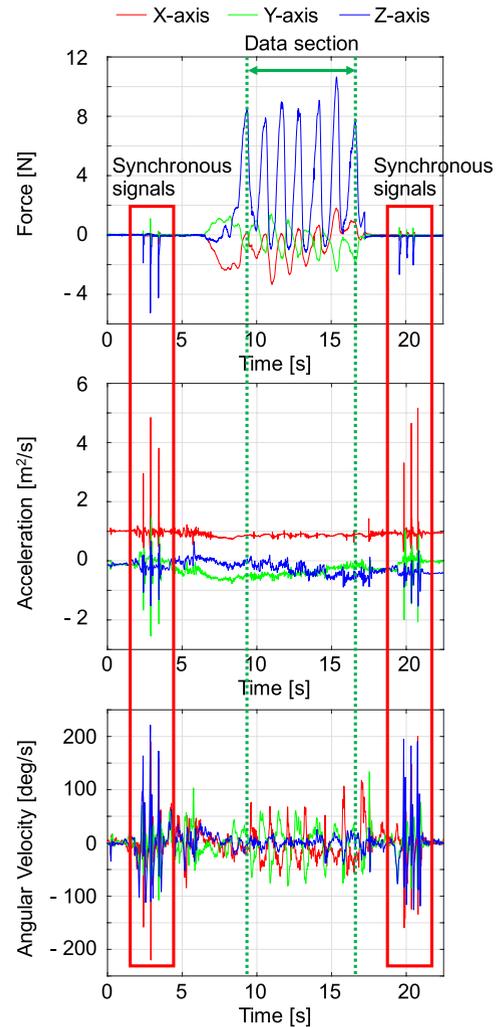


FIGURE 10. Example of synchronization and extraction of the data section for analysis.

as shown in Fig. 10. Based on the Z-axis force, the motion section between the maximum values of the first and seventh strokes was extracted and used for the analysis, as shown in Fig. 10. This preprocessing was performed because the duration from the synchronous signals to the first stroke varied for each participant.

TABLE 1. Description of sensor measurement values in the forearm rotation motion.

Axis item	Description
X-axis force	Force exerted by the blade of the hand scaler on the tooth surface from the buccal side
Y-axis force	Force exerted by the blade of the hand scaler on the tooth surface to pharynx direction
Z-axis force	Force exerted by the hand-scaler blade on the tooth surface in the direction of pulling up the hand-scaler blade
X-axis acceleration	Acceleration of the hand scaler in the direction it is pulled up
Y-axis acceleration	Acceleration of the hand scaler moving toward the tip
Z-axis acceleration	Acceleration when the hand scaler is tilted by forearm rotation moving in the direction of the tip and vertical from the long axis of the hand scaler
X-axis angular velocity	Angular velocity of rotation about the long axis of the hand scaler
Y-axis angular velocity	Angular velocity of rotation on a plane parallel to the long axis of the hand scaler and vertical to the blade
Z-axis angular velocity	Angular velocity of rotation on a plane parallel to the long axis of the hand scaler and parallel to the blade

TABLE 2. Features values.

No	Symbol	Description
1	Afx	Average of force on the X-axis
2	Afy	Average of force on the Y-axis
3	Afz	Average of force on the Z-axis
4	Sfx	Standard deviation of force on the X-axis
5	Sfy	Standard deviation of force on the Y-axis
6	Sfz	Standard deviation of force on the Z-axis
7	Aax	Average of acceleration on the X-axis
8	Aay	Average of acceleration on the Y-axis
9	Aaz	Average of acceleration on the Z-axis
10	Sax	Standard deviation of acceleration on the X-axis
11	Say	Standard deviation of acceleration on the Y-axis
12	Saz	Standard deviation of acceleration on the Z-axis
13	Agx	Average of angular velocity on the X-axis
14	Agy	Average of angular velocity on the Y-axis
15	Agz	Average of angular velocity on the Z-axis
16	Sgx	Standard deviation of angular velocity on the X-axis
17	Sgy	Standard deviation of angular velocity on the Y-axis
18	Sgz	Standard deviation of angular velocity on the Z-axis

2) FEATURE EXTRACTION

The average and standard deviation, which represented the magnitude of motion and the scattering of the magnitude, of force, acceleration, and angular velocity in each of the three axes were calculated as features of 18 items, as shown in Table 2. Each feature was calculated for each trial from the sectional data obtained during preprocessing. We calculated 18 features, each for a total of 20 trials per participant (10 trials using the tip and 10 trials using the middle). In comparison with the stable repetitive strokes using the tip, the strokes performed using the middle of the blade showed distinct characteristics. For example, when students used the middle, the blade may slide on the tooth surface, causing a sudden change in the acceleration or angular velocity. The blade may be caught on the tooth surface, thereby increasing the force applied. Therefore, we selected features that reflected the magnitude of motion and scattering of the magnitude.

3) CLASSIFICATION OF THE CONTACT POSITION OF THE BLADE

To identify whether the tip or middle was in the contact with the tooth, we used SVM [24], which can determine an appropriate discriminative boundary even with a small amount of training data. We trained and tested the data separately for each participant to account for differences among participants and verified whether it was possible to

TABLE 3. C parameters.

SVM predictor	C
IMU+F features	1
IMU features	1
F features	10
When the first rank accuracy was achieved by one feature of IMU	0.1
When the first rank accuracy was achieved by two features of IMU	0.1
When the first rank accuracy was achieved three features of IMU	1
When the second rank accuracy was achieved by two features of IMU	1
When the third rank accuracy was achieved by two features of IMU	10

classify the scaler blade contact with the tooth based on the extracted features. The SVM was implemented using MATLAB R2021b, MATLAB toolbox statistics, and the Machine Learning ToolboxTM (MathWorks, Inc.). A linear kernel was used, and five-fold cross-validation was performed. Data were standardized as mean = 0 and standard deviation = 1. We attempted cross-validation using all folds for all participants using all six of [0.001, 0.01, 0.1, 1, 10, 1000] as the SVM hyperparameter C , and chose the C that achieved the highest average accuracy. We analyzed the accuracy value that corresponded to the highest average accuracy. Table 3 lists the values of SVM hyperparameter C used in each case.

4) COMPARISON OF CLASSIFICATION ACCURACY

First, we examined whether the model accuracy using features obtained with only one type of sensor was as high as that obtained using both types of sensors together. For this purpose, the accuracy obtained when using 18 features from the IMU and force sensor (*hereafter referred to as IMU+F features*) as predictors was compared with the accuracy of a model using the 12 features of the IMU alone (*hereafter referred to as IMU features*) and that of a model using the six features of the force sensor alone (*hereafter referred to as F features*) by the STEEL test [25].

Furthermore, we examined the minimum number of single-sensor feature combinations that yielded the same level of accuracy as that obtained using IMU+F features to determine whether data processing and memory could be further reduced. The comparison procedure is shown in Fig.11 and below.

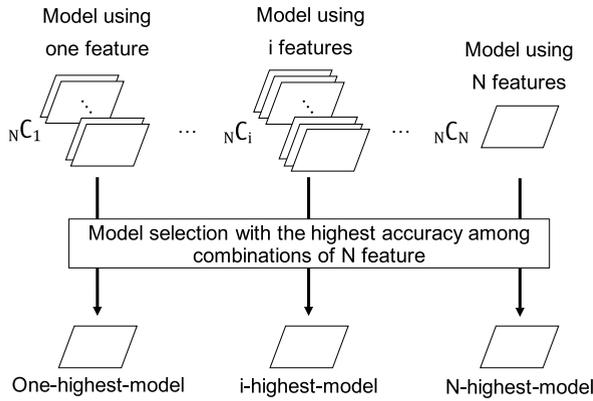


FIGURE 11. Definition of i-highest model.

TABLE 4. STEEL test comparing the classification accuracy using IMU alone and force sensor alone versus IMU and force sensor.

Comparison	t.value	p.value
IMU + Force Sensor : Force Sensor	2.4225	0.0145
IMU + Force Sensor : IMU	0.3567	0.5160

TABLE 5. STEEL test of classification accuracy by IMU+F features and features using IMU alone.

Comparison	t.value	p.value
IMU+F features : one IMU feature	3.6456	0.0004
IMU+F features : two IMU features	1.9705	0.0613

- (i) Models with i ($i = 1, \dots, N$) features from a single-sensor were developed. N equals 6 and 12 for the force sensor and the IMU, respectively.
- (ii) A model with the highest accuracy was determined for each model group with i ($i = 1, \dots, N$) features. The models were referred to as i -highest models for each sensor.
- (iii) i -highest models and IMU+F model were compared by STEEL test. The minimum number of i in which the null hypothesis is validated with i -highest model was calculated.

A one-tailed test was conducted with the null hypothesis “average accuracy of 18 predictors (IMU+F features) = average accuracy of N predictors (features)” and the alternative hypothesis “average accuracy of 18 predictors (IMU+F features) > average accuracy of N predictors (features)”. A p -value more than 0.05 validated the null hypothesis and rejected the alternative hypothesis, implying that the average accuracy of 18 predictors (IMU+F features) and the average accuracy of N predictors (features) were equivalent.

III. RESULTS

A. CLASSIFICATION ACCURACY OF THE CONTACT POSITION OF THE BLADE

The average accuracy of each participant according to the SVM is shown in Fig. 12. This figure shows the results for the IMU+F, IMU, and F features as predictors. The average overall participants of the IMU sensor and force sensor, IMU sensor alone, and force sensor alone were $97.1 \pm 4.7\%$, $95.9 \pm 6.9\%$, and $88.8 \pm 14.2\%$, respectively.

B. COMPARISON OF ACCURACY BETWEEN SENSOR COMBINATIONS

The results of the STEEL test comparing the accuracy of 18 predictors (IMU+F features) with the accuracy of 12 predictors (IMU features) and six predictors (F features) are shown in Table 4. No significant difference was observed between the accuracy of the 18 predictors (IMU+F features) and the accuracy obtained with IMU alone ($p = 0.52$). However, the accuracy obtained with the force sensor alone was significantly different from the accuracy of the 18 predictors (IMU+F features) ($p = 0.01$).

C. COMBINATION OF MINIMUM SENSOR CONFIGURATION AND MINIMUM NUMBER OF FEATURES

The accuracy obtained with the force sensor alone was significantly different from that of the IMU and force sensor. We show the results of the IMU that was able to examine the minimum combination of features. Fig. 13 shows the average accuracy of each participant using the IMU+F features and one and two IMU features as predictors. Table 5 shows the results of the STEEL test comparing the accuracy of the IMU and force sensor with that of the IMU alone. The accuracy obtained when IMU+F features were used as predictors was significantly different from that obtained when one IMU feature was used as a predictor ($p = 0.0004$), but not significantly different from that obtained when two IMU features were used as predictors ($p = 0.06$). Table 6 shows the top three combinations of two IMU features. All these combinations did not significantly differ from the accuracy of IMU + F features. The average acceleration along the X-axis (A_{ax}) was always included in these combinations.

IV. DISCUSSION

Using the linear SVM, the contact between the tip or middle of the hand-scaler blade with the tooth could be classified with an accuracy of 97.1%. Unlike the blind spots associated with the use of a camera, the proposed simulator did not involve this problem and the IMU+F features showed high accuracy. Therefore, we considered this approach to have high potential for clinical application.

The accuracy obtained with the force sensor alone was significantly different from that obtained with both the IMU and the force sensor. In contrast, the accuracy obtained using the IMU alone was not significantly different from that obtained with the IMU and the force sensor. Thus, the sensor configuration can be reduced from the combination of an IMU and force sensor to one IMU. Since the force sensor was attached directly to the target tooth of the hand-scaling simulator, space was needed under the teeth to mount the force sensor, and the existing mannequin’s structure, which imitates the head, had to be redesigned. These changes in design would not be necessary when a force sensor is not required.

To simplify the data processing process, we also examined the minimum number of IMU features that maintained the same level of accuracy as that obtained with the IMU+F features. The results showed that the accuracy of combinations

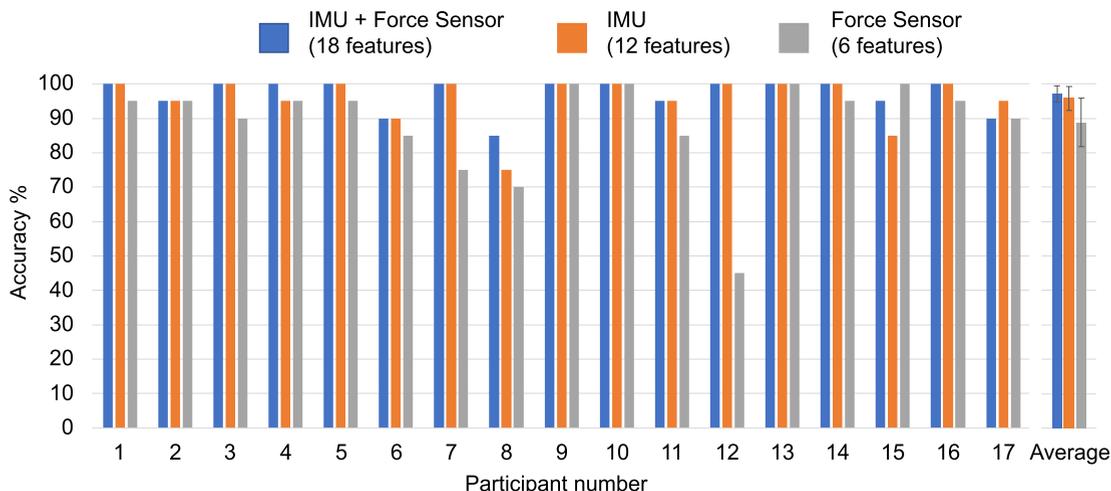


FIGURE 12. Classification accuracy using the IMU and/or force sensor.

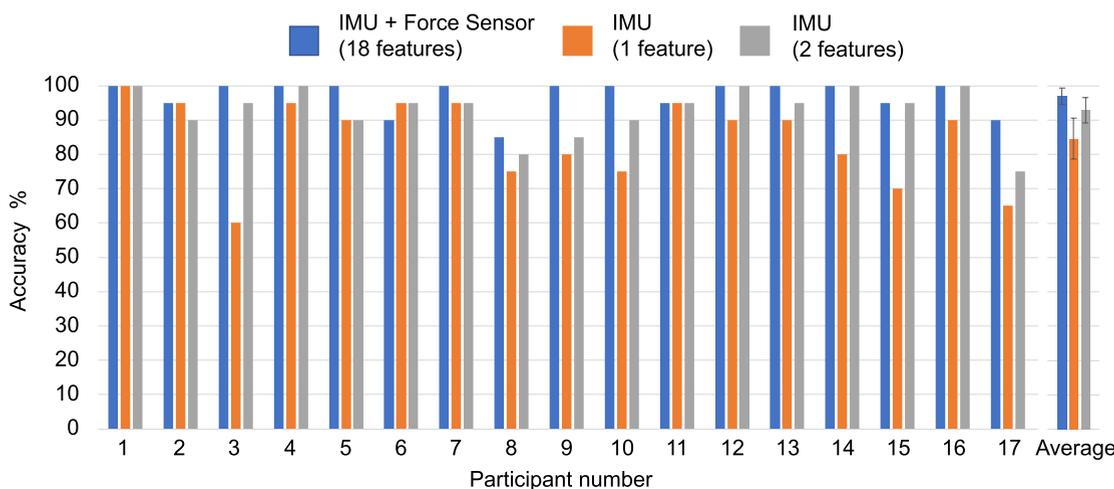


FIGURE 13. Classification accuracy of the IMU+F and IMU feature combinations.

TABLE 6. Combinations of two IMU features with no significant difference in classification accuracy in comparison with IMU+F features.

Ranking	Symbols											
	Aax	Aay	Aaz	Sax	Say	Saz	Agx	Agy	Agz	Sgx	Sgy	Sgz
1	○					○						
2	○		○									
3	○										○	

of only two IMU features was not significantly different from that of the IMU+F features. This can simplify the data processing process. Using a combination based on the accuracy of the first rank shown in Table 6, the classification can be made by measuring the values for the acceleration X-axis and acceleration Z-axis. The processing required for data measurement, feature value calculation, and SVM can be reduced with two axes than with six axes, and the storage capacity of the data can also be saved. These advantages can make a difference in the implementation stage, e.g., when attempting to install functions on a small low-spec single-board computer in an oral cavity model.

In addition, the combinations of two IMU features shown in Table 6 always included the average acceleration in the X-axis, suggesting that it is an important data axis that shows differences in the hand-scaling motion and can be used. The X-axis acceleration reflects the magnitude of the vertical motion of the hand-scaler blade along the tooth surface. When students use the middle during hand scaling, the blade often cannot move smoothly and slips on the tooth surface. Consequently, the motion of the blade is very wide, which is different from the stable stroke when using the tip. A similar motion was observed by the participants in the experiment. When such a motion is observed, the system advises reconfirming

whether the tip is in contact with the tooth surface, which will help improve the effectiveness of self-learning.

A limitation of this study is that the participants in the experiment performed hand-scaling only at a specific site of a specific tooth. Therefore, the potential of this method for identifying the state of contact between the tip and tooth for a different tooth or part is unknown. To improve the generalizability of the results of this study, future studies should aim to verify whether this approach can be used with different teeth, parts, and hand scalers.

V. CONCLUSION

The purpose of this study was to verify whether the features acquired from the IMU attached to the hand scaler and the force sensor attached to the target tooth can be used to identify whether the tip of a hand-scaler blade is in contact with the tooth. The IMU and force sensor were used to measure motion while avoiding the problem caused by the gingiva or buccal mucosa obstructing the view of the tooth on the camera image. Data were obtained during hand scaling with forearm rotation. We used SVM to classify whether the tip or the middle of the hand-scaler blade was in contact with the tooth during hand scaling by using features from two types of sensor data. The results showed that classification with a high accuracy of 97.1% was possible. This study is the first to identify the contact of the blade of a hand scaler with the tooth by using an IMU and force sensor. Development of a simulator equipped with the contact-classification method proposed in this study will allow classification of and feedback for the contact state between the tip and tooth surface and the application of this approach as an easily usable self-learning simulator.

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TOMOKO YUI (Graduate Student Member, IEEE) received the M.E. degree from the Robotics Laboratory, Division of Information Science, Nara Institute of Science and Technology, Nara, Japan, in 2020, where she is currently pursuing the Ph.D. degree with the Human Robotics Laboratory. Her research interests include human modeling and simulation in medical education.



SUNG-GWI CHO (Member, IEEE) received the M.S. and Ph.D. degrees in engineering from the Nara Institute of Science and Technology, Japan, in 2017 and 2020, respectively. From April 2020 to March 2022, he was an Assistant Professor with the Graduate School of Science and Technology, Nara Institute of Science and Technology. Since April 2022, he has been an Assistant Professor with the Division of Electronic Engineering, School of Science and Engineering, Tokyo Denki University. His research interests include human-machine interface, human sensing, and human activity recognition.



JUN TAKAMATSU (Member, IEEE) received the Ph.D. degree in computer science from The University of Tokyo, Japan, in 2004. From 2004 to 2008, he was with the Institute of Industrial Science, The University of Tokyo. He was a Visiting Researcher with Microsoft Research Asia, in 2007. From 2008 to 2020, he was an Associate Professor with the Nara Institute of Science and Technology, Japan. He was a Visitor at Carnegie Mellon University, in 2012 and 2013, and a Visiting Scientist at Microsoft, in 2018. He is currently working as a Senior Researcher with Applied Robotics, Microsoft. His research interests include robotics, including learning-from-observation, task and motion planning, feasible motion analysis, 3D-shape modeling and analysis, and physics-based vision.



YUKI SATO received the Ph.D. degree in arts and sciences from The University of Tokyo, Japan, in 2012. He worked as a Postdoctoral Researcher at Waseda University, from 2012 to 2014, at the National Rehabilitation Center for Persons with Disabilities, from 2014 to 2018, and at Ritsumeikan University, from 2018 to 2020. He was a Research Assistant Professor at Ritsumeikan University, from 2020 to 2021, and an Assistant Professor at the Nara Institute of Science and Technology (NAIST), from 2021 to 2022. Since 2022, he has been an Assistant Professor with Ibaraki University, Japan. His research interests include study of embodied cognitive science, particularly extended embodiment (i.e., sense of agency and ownership), and motion sickness.



TAKAHIRO WADA (Member, IEEE) received the B.S. degree in mechanical engineering, the M.S. degree in information science and systems engineering, and the Ph.D. degree in robotics from Ritsumeikan University, Japan, in 1994, 1996, and 1999, respectively. In 1999, he became an Assistant Professor at Ritsumeikan University. In 2000, he joined Kagawa University, Takamatsu, Japan, as an Assistant Professor with the Department of Intelligent Mechanical Systems Engineering, Faculty of Engineering. He was promoted to an Associate Professor, in 2003. He joined as a Full Professor with the College of Information Science and Engineering, Ritsumeikan University, in 2012. Since 2021, he has been a Full Professor and the Director of the Human Robotics Laboratory, Division of Information Science, Nara Institute of Science and Technology (NAIST), Japan. In 2006 and 2007, he spent half a year as a Visiting Researcher at the University of Michigan Transportation Research Institute, Ann Arbor. His current research interests include robotics, human-machine systems, and human modeling. He is a member of ITSS, SMC, EMBS, and RAS, the Robotics Society of Japan (RSJ), the Society of Automotive Engineers of Japan (JSAE), the Society of Instrument and Control Engineers (SICE), and the Japan Society of Mechanical Engineers (JSME). He received the Best Paper Award from JSAE, in 2008 and 2011, and the Outstanding Oral Presentation from the Society for Automotive Engineers (SAE), in 2010.



YASUAKI ORITA received the M.S. and Ph.D. degrees in engineering from Ritsumeikan University, Japan, in 2019 and 2022, respectively. Since April 2022, he has been an Assistant Professor with the Graduate School of Science and Technology, Nara Institute of Science and Technology. His research interests include sensor recognition, control, and their applications.



MING DING (Member, IEEE) received the M.S. and Ph.D. degrees in engineering from the Nara Institute of Science and Technology, Japan, in 2007 and 2010, respectively. In April 2010, he joined as a Postdoctoral Researcher at the Department of Mechanical Engineering, Tokyo University of Science. From October 2011 to February 2014, he was a Researcher with the RIKEN-TRI Collaboration Center for Human-Interactive Robot Research, RIKEN. Since March 2014, he has been the Designated Assistant Professor with the Graduate School of Engineering, Nagoya University, Japan. Since May 2015, he has been an Assistant Professor with the Graduate School of Information Science, Nara Institute of Science and Technology. Since November 2019, he has been as a Designated Associate Professor with the Institutes of Innovation for Future Society, Nagoya University. His current research interests include robot control, human modeling, and human-machine interface.



TSUKASA OGAWARA (Life Member, IEEE) received the B.S. and Ph.D. degrees from The University of Tokyo, Japan, in 1983. From 1983 to 1998, he was with the Electrotechnical Laboratory, Ministry of International Trade and Industry, Japan. From 1993 to 1994, he was a Humboldt Research Fellow at the Institute for Real-Time Computer Systems and Robotics, University of Karlsruhe, Germany. He joined the Nara Institute of Science and Technology, Nara, Japan, in 1998, where he is currently a Professor with the Division of Information Science. He is also the Vice President of the Nara Institute of Science and Technology and the Dean of the Graduate School of Science and Technology. His research interests include human-robot interaction, dexterous manipulation, human modeling, and bio-inspired robotics.

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