DOCTORAL DISSERTATION

Modeling hand-scaling skill of dental hygienist and its application to skill training

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Abstract

Students who wish to become dental hygienists learn basic hand-scaling skills i.e., a precise intraoral operation of instruments, through repeated practices using a human head model. Hand scaling is a dental procedure in which the blade of an instrument (known as a hand scaler) is used to scrape stains from the teeth surfaces. This skill follows the standard teaching guidelines mentioned in textbooks and is supplemented by verbal feedback and non-verbal feedback based on the experience of teachers who play an important role. However, feedback is not available when teachers are not available, and the effectiveness of education varies depending on their capability. This study aims to model the most basic and essential skills related to the contact between the blade of a hand scaler and tooth surfaces based on kinematic and mechanical information and verify the effectiveness of a developed skill-training method based on the evaluation of an exemplary-motion-based model.

This study is organized as follows:

Chapter 2 describes the development of a system for measuring hand scaling by attaching a force sensor and inertial measurement unit (IMU) to a conventionally used human head model and hand scaler. The experiments considering dental hygienists and dental hygiene students confirmed that the measurement values exhibited motion characteristics, e.g., the repetitive motion of the hand scaler, and the possibility of discriminating subjects with different skill levels using the force applied by the hand scaler blade to the tooth surface was demonstrated.

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In Chapter 3, assuming students who have experienced training to some extent, motion modeling for each student was conducted based on the assumption that data are available to allow teachers to label success or failure based on the motions performed by the students. It was confirmed that a two-class classification model using a support vector machine (SVM) with features obtained from the force sensor and IMU is capable of highly accurate motion classification (17 subjects; an average classification accuracy of 97.1%). The additional investigation confirmed that the same classification accuracy can be maintained with features obtained only from the IMU and demonstrated the possibility of reducing the number of sensors.

Chapter 4 describes the development of a model based on the hand scaling motion of a dental hygienist using a one-class SVM, assuming that it would be applied to students in the early stages of training. In addition, a skill training method that helps to improve modeled motions using the classification model was proposed. Skill-training experiments in which experimental groups were divided based on the advices of the proposed method were conducted, and it was confirmed that the groups that received advices significantly improved their skills.

Keywords:

Dental hygienist, Hand scaling, Motion measurement, Inertial measurement unit (IMU), Force sensor

歯科衛生士のハンドスケーリング技術のモデル化と 技能訓練への応用*

由井 朋子

内容梗概

歯科衛生士を志す学生は、人の頭部模型を使用した反復練習を通して、口 腔内での緻密な器具操作であるハンドスケーリング(ハンドスケーラーと呼 ばれる器具の刃部で、歯表面の汚れを掻き取るような歯科処置の1つ)の基 礎技術を習得する.この技術の教育では、教本による標準的な指導指針に 沿って行いつつも、これを補う形で行われる教員の経験に基づいた言語的、 非言語的フィードバックが重要な役割を果たしている.また、教員不在時に はそのフィードバックが得られず、教員の力量によって教育効果に差がある という問題がある.そこで本研究では、最も基本的で重要とされるハンドス ケーラー刃部と歯表面の接触様態に関する技術を対象に、運動学情報、力学 情報から技術をモデル化すること、さらにハンドスケーリングの手本動作モ デルを用いた技能評価を行い、その結果を用いた技能訓練手法を開発しその 効果検証を目的とする.

本研究の内容は以下の通りである.

第2章では、従来用いられてきた頭部模型およびハンドスケーラーに力セン サと慣性計測装置(IMU)を取り付けることで、ハンドスケーリングを計測す るシステムを開発した、歯科衛生士と歯科衛生士学生を対象とした被験者実 験の結果、計測値にハンドスケーラーの反復移動などの動作特徴が現れるこ とを確認し、ハンドスケーラー刃部が歯表面へ加える力を用いて技能レベル が異なる被験者の判別可能性を示した.

第3章では、ある程度の訓練を経てきた学生に応用することを想定 し、学生自身が実施した動作を元に教員が成功失敗のラベリングを行 えるデータがあることを前提に、学生個人毎の動作モデリングを行っ

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た. カセンサとIMUから得られる特徴量を利用して単純なサポートベク ターマシン(SVM)を用いた2クラス分類モデルで,高い精度の動作分類が可 能(被験者17名,平均分類精度97.1%)であることを確認した.追加調査の結 果,IMUのみから得られる特徴量でも同等の分類精度が維持できることを確 認し,センサの削減可能性も示した.

第4章では、極めて訓練初期段階にある学生に応用することを想定し、 歯科衛生士のハンドスケーリング動作を元に、手本動作モデルを1クラ スSVMを用いて作成した.さらにその分類モデルを用いて動作の改善アドバ イスを行う技能訓練手法を提案した.提案手法によるアドバイスの有無で実 験群を分けて技能訓練実験を行ったところ、アドバイス有り群で有意な技能 向上を確認した.

キーワード:

歯科衛生士、ハンドスケーリング、動作計測、慣性計測装置、力センサ

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Chapter 1

Introduction

1.1. Background

In Japan, a law with regard to the promotion of dental and oral health exists. Preventing oral diseases can contribute to a smooth oral intake and the extension of healthy life expectancy.

A dental hygienist is one of the dental medical professions that help prevent oral diseases. Students who want to become dental hygienists must acquire knowledge and skills in a minimum of 3 years. However, the technique used by dental hygienists involves delicate manipulation of instruments for treating an oral cavity. Mastering the technique is not an easy task. Textbooks on technical education are available, and the instrument to be used is described, along with its purpose and procedures. However, it does not detail operational characteristics, e.g., the operating pressure of the instrument, and the teacher summarizes teaching points and uses visual materials, e.g., models and diagrams. The teacher models include teaching points that cannot be verbalized. Students acquire various information based on the use of their own sense of sight and fingers and acquire skills through repeated practice. Sato et al. [1] noted that it is necessary to pay attention to the structure and explanation of visual materials when they are used in education, considering that learners do not perceive visual materials in the same way as educators. Teachers feel that it is difficult to guide students.

Currently, simulation is widely used in medical education [2, 3, 4]. Simula-

1.2 Purpose

tion practice plays an important role in the acquisition of surgical skills because it allows sufficient practice before students are allowed to treat patients [5, 6]. Practice is important for mastering surgical skills [7], and simulation education is a safe, efficient, and ethical practice method [8]. Students can learn from their mistakes without the fear of harming patients [9]. Simulation education can serve as an efficient and ethical method for training students to deliver safe medical care to patients [10]. In addition, simulations are being widely applied to education, and used for technical evaluation [11] to enable detailed feedback and objective verification [12, 13].

In the technical education of dental hygienists, a human head model is prepared as self-study content (one of the simulation education). However, this model does not provide feedback even if some operations are performed. Owing to time constraints, it is difficult for teachers to be present for all the exercises, and students end up doing inefficient self-study without being sure whether their operations are correct.

1.2. Purpose

A simulator that can provide feedback and evaluate the technical training of dental hygienists can help to improve the environment for practicing inefficient techniques. Therefore, this study aims to model the hand-scaling motion for a simulator that enables self-study and examine its application for technical practice. The target work is hand scaling. A method is proposed to measure the hand-scaling motion and make a function to judge the motion based on the measured values. A motion measurement system attached to a force sensor and inertial measurement device (IMU) is constructed to quantitatively represent motions. After verifying the effectiveness of the measurement system, the motion judgment function is examined by creating a motion classification model using a support vector machine (SVM). There are two models to be created: one that classifies the contact relationship between the tip of the hand-scaler blade and tooth surface, and another model that classifies the modeled motion and other motions. Applicability to training systems for models that classify the modeling motion and the other motion is demonstrated as well.

1.3. Hand scaling

Hand scaling [14, 15, 16, 17, 18, 19] is the task of removing tartar and other stains, using a device known as a hand scaler. Various shapes of hand scalers are determined according to the part of the tooth to be treated.

It is a process that mechanically removes stains, e.g., calculus adhering to the tooth surface, using the tip of the blade of the hand scaler. This is one of the most important tasks of a dental hygienist, and it is difficult to master this task because it requires proper skills to operate the hand scaler to accurately remove deposits firmly attached to the tooth surface. The hand-scaling process is described below:

- Grip the hand scaler like a writing instrument (Figure 1.1). The ring finger of the hand holding the hand scaler is applied to the adjacent tooth as a fulcrum.
- The tip of the blade of the hand scaler should range from 1 to 2 mm, as shown in Figure 1.2. As shown in Figure 1.3, the cutting edge makes a continuous stroke of 2 3 mm (also known as a walking stroke) along the tooth surface. The trajectory of the tip. It is important to move them so that they slowly overlap.
- Figure 1.4 shows the rotating motion of the forearm, which is the basic motion of the hand scaler. The pronation and supination of the forearm correspond to the action of lowering the blade to the stroke start position and raising the blade to the stroke end position. The repetition of stable motions is ideal. The tip removes dirt attached to the surface of the tooth by applying lifting force while pressing against the tooth surface.



Figure 1.1. Technique to hold a hand scaler



Figure 1.2. Correct use of the blade for hand scaling



Figure 1.3. Strokes during hand scaling



Stable repetitive motion is ideal

Figure 1.4. Hand-scaler operation: Forearm rotation

1.4. Related studies

Studies on dentistry, hand scaling, and fields other than dentistry using IMU are presented as references for motion measurement and evaluation. In dentistry, simulators using augmented reality (AR) and virtual reality (VR) play an important role in education at dental schools and graduate schools [20]. Although these simulators possess some disadvantages [21], they are considered to be valuable educational tools that can enhance conventional educational methods [22, 23].

1.4 Related studies

However, in this study, the focus is on IMUs as one of the motion measurement technologies to develop a new simulator.

1.4.1. Dentistry

General dentistry

In dentistry, students at a beginner level cannot practice their skills on humans, because it is unethical and unsafe. Therefore, training and simulation in a virtual space are widely used [24]. For example, visual information is reproduced by AR and VR, and haptic technology produces the sensation of manipulating handy instruments. One such operation was performed on a tooth displayed on a two-dimensional screen for periodontal examination using an input portion that mimics an instrument [25, 26]. Simodont [27, 28, 29] and Periosim [30, 31] are commercialized simulators that use haptic technology dedicated to dental care. These simulators can simulate periodontal examinations and the removal of the affected portions of the teeth, and reproduce the relative positional relationship between the teeth and instruments and the sensation of hand and finger during contact. Commercialized systems can be applied to various training by creating new content for the target treatments.

Another engineering study on dentistry relevant to this study is the application of forces on the teeth. In orthodontics, several studies have been conducted to measure the force applied to the teeth using orthodontic instruments [32, 33, 34, 35]. These studies help examine the dentist's technique by evaluating orthodontic forces by attaching a force sensor to the target tooth. Another study has established a prediction model of orthodontic moments by attaching force sensors to orthodontic instruments [36]. Outside of orthodontics, in one of the studies, a single force sensor was attached under a jaw model with teeth implanted to measure the force applied to the teeth using an oral cleaning instrument [37]. As it is possible to estimate the amount of force applied to each tooth with a single force sensor instead of force sensors attached to individual teeth, the time and effort required for installation can be reduced.

1.4 Related studies

Hand scaling

To evaluate hand scaling, the force to pinch a hand scaler is measured using a sensor attached to the handle and evaluated [38, 39]. The hand scaler is held such to pinch using fingertips. Myoelectricity has been considered for evaluation because hand scaling causes physical fatigue and other problems when working for long periods [40]. In addition, studies that evaluate the force exerted on the teeth using the hand-scaler blade during hand scaling to analyze the force used to efficiently remove tartar from the tooth surface are available [41, 42].

Furthermore, studies on hand-scaling training include the application of haptics technology and VR. There is a study that enables the hand-scaling practice on teeth arranged on a jaw model [43]. In this process, a user grasps a part of the haptic device as if holding a hand scaler, while performing hand scaling on a tooth model with only three teeth in a row. Another study proposed a visualization system for the tip of the hand-scaler blade using a camera [44]. The camera captures the hand-scaling operation including an AR marker attached to the rear end of the hand-scaler gripping part and a model of a head with a tooth model. The AR marker is used to estimate the motion of the tip of the hand-scaler blade, and a virtual hand scaler is displayed on the captured image as if it were pasted on top. The motion of the blade hidden inside the mouth can be visualized.

1.4.2. IMUs

IMUs have been widely used for human activity recognition [45], as they have been miniaturized. Several studies on the use of IMUs have been conducted to enable the acquisition of human motion information and use of machine learning algorithms to achieve motion classification. In the sports field, IMUs are used for coaching by measuring the motions of athletes [46, 47, 48, 49]. In the medical field, they are widely used to evaluate suture motions in surgical procedures [50], classify the motion of mice used in drug discovery experiments [51], and classify the movements of patients with Parkinson's disease [52].

One study has utilized the advantage of the IMU's ability to recognize and measure minute motions, enabling the recognition and classification of gestures by acquiring information related to hand motions [53]. The orientation and posture

1.5 Dissertation Outline

of a single finger can be acquired as well, and this mechanism can be applied to hand rehabilitation and human-computer interaction.

1.5. Dissertation Outline

In Chapter 2, a system that can quantitatively measure hand-scaling motions has been proposed. In addition, experimental results have been considered to verify whether hand scaling, which is a very fine motion, can be evaluated based on the measured values. Figure 1.5 shows that the system proposed in Chapter 2 helps in modeling, which is explained in Chapters 3 and 4.

Chapter 3 discusses the application of the measurement system proposed in Chapter 2 to demonstrate the possibility of judging hand-scaling motion. In the past, simulators for hand-scaling practice were available; however, there were not many studies on the process to feed back the results of practice. Therefore, in this study, the results of verifying whether it is possible to determine whether the tip of the hand-scaler blade and tooth surface are in contact, which is one of the essential teaching points during hand scaling, have been demonstrated. Using an SVM, one of the machine learning algorithms, the possibility of judging the correctness of hand scaling in two-class classification based on individual training data has been verified. The participants are dental hygienist students who had practiced to some extent. The reason for using individual learning data is that the dental hygienist students have practiced on the forehead model to some extent and established their own motions.

As it is possible to judge the hand-scaling motion (as suggested in Chapter 3), Chapter 4 describes an experiment that has been conducted by modeling the hand-scaling motion of one dental hygienist. With regard to learning data, motion data measured by a single dental hygienist is used as teacher data. Then, based on the feedback from the measured values, it was verified whether the data of the test participants, assuming a beginner, can approximate the motion of the learning data. It has been examined whether the proposed system would allow beginners who have not yet mastered hand-scaling motions to practice efficiently by simulating the motions of a dental hygienist.

Chapter 5 discusses the effectiveness of the hand-scaling model and its appli-

cability as a hand-scaling simulator.



Figure 1.5. Chapter relationship chart

1.6. Importance of Modeling

Currently, motions taught in hand scaling do not exhibit uniformity. While the teaching of hand scaling follows the standard instructional guidelines of textbooks, verbal feedback, and nonverbal feedback based on teachers' experience that complement these guidelines play an important role. As a result, differences are created by instructing faculty teachers. Even if hand-scaling motion can be measured as quantitative data, the evaluation function of motion cannot be completed without a model of correct motion to judge whether the motion is correct or incorrect.

Therefore, the modeling of motions as a means of representing motions has been proposed in this study. By modeling a motion, the correct motion including instructional points can be clarified. Hand scaling possesses kinematic and dynamic information. This can include technical points that can be taught linguistically and non-verbally.

Two models have been created and tested in this study. The training phase changes depending on the progress of the training, as shown in Figure 1.6. The figure represents stages for students who are acquiring skills: beginners who have started practicing and novices who have repeated a certain amount of practice. Although the points to be taught are the same, the points that should be empha-

1.6 Importance of Modeling

sized at each stage of learning change. For example, for beginners who have just started training, it is important to be able to correctly hold and move a hand scaler, considering an exemplary motion as a guide. For novices with repeated training, it is important to be able to precisely control the tip of the hand scaler on the surface of the target tooth in addition to establishing their own motions.

Therefore, a technical model has been created with regard to the contact between the hand-scaler blade and tooth surface at first. The technique that this model targeted requires the fine operation of a hand scaler to fulfill the original purpose of hand scaling, which is to efficiently remove stains from the surfaces of the tooth. For training data, features obtained by measuring the hand-scaling motions of individual students can be used as the focus of this task is on students at the novice level. It is possible to generate data that allows the faculty to label success or failure based on motions performed by the students themselves.

Next, an exemplary motion model of hand scaling has been created. Students at the beginner level practice the operation of large motions, which are basic motions, e.g., the forearm rotation motion to move the hand scaler, by imitating the model of the instructor. These students have not mastered hand-scaling motions at this stage. Therefore, the training data are modeled based on the hand-scaling motion of a dental hygienist as a teacher who can perform the modeled motion. The model is created to acquire motion that is highly similar to the modeled motion at a stage when one's motion has not been established.

The motions of the technical parts of hand scaling are wide-ranging, with some motions being fine and others being comparatively large. In addition, the motions (student's or teacher's motion) to be modeled change during the training phase. Thus, the usefulness of the model considering its educational training phases has been examined.

The two models developed in this study are assumed to be used in different training stages. The models are not complementary, as they train various motion skills. The exemplary motion model is the teacher model, and the contact relationship model between the hand-scaler blade and tooth surface is the student model. The teacher model is used in the first stage of student training, and the student model is used in the middle stage. In the mid-term of training, they reach a level where they can perform motions naturally without thinking; thus, their

1.7 Contributions

own motion characteristics are included in their hand-scaling motions. For that reason, my recommendation would be to use the student model in the middle stage of the training.



Figure 1.6. Training phases and chapters

1.7. Contributions

The main contributions of this study are as follows:

- A measurement system for hand-scaling motions based on quantitative data is created. The IMU is attached to the handle of the hand scaler to measure the motion of the hand scaler, and the force sensor is attached to the tooth to be hand-scaled to measure the hand-scaling force on the tooth.
- Two models are created: one for the contact between the hand-scaler blade and tooth and the other for the exemplary motion. The models are modeled based on the measurements obtained from the IMU and force sensor, considering the training phase for the first time. The SVM is used for model creation. The model of the contact of the training data with the teeth of the hand-scaler blade is modeled using the training data of the individual because a novice possesses an established behavior of their own. The exem-

plary motion model is created for beginners because they have not learned the motion at all; a motion model by a dental hygienist is created for them.

- The exemplary motion model can be effective when utilized for education. The model can be used to determine if a motion is exemplary or not and provide advice on the modeled motion. Participants are divided into groups with and without advice, and when the groups were compared, it was found that the group with advice improves hand-scaling motion more than the group without advice.
- The main contribution of this study is the modeling of hand-scaling motion considering the training phase. Based on the results of this study, a standard educational system through modeling can be proposed. Depending on the learning stage, there are two stages: one is to practice approaching the exemplary motion, and the other is to learn the appropriate motion including one's motion characteristics. The concept of creating a model that includes individual differences and the actual creation of such a model are the characteristics of this study.

1.8. Publication Note

The parts of the work described in this paper have been published in previous publications. The proposal and verification of the measurement system for hand-scaling motion explained in Chapter 2 were presented in [54]. The judgment based on the identification of the contact between the tip of the hand-scaler blade and tooth surface during hand-scaling operation explained in Chapter 3 was published in [55].

Chapter 2

Measurement of hand-scaling motion

2.1. Introduction

In this chapter, I develop a measurement system to quantify the skills of dental hygienists and evaluate them by comparing the results of professional hygienists and students. I equip a jaw model with a force sensor to measure the force when a hand scaler touches a target tooth, as shown in Figure 2.1. I also attach an inertial measurement unit (IMU) sensor to the bottom of the hand scaler to measure the hand-scaling motion. In the experiment, I measure the hand-scaling motions of several participants with different levels of job experience. The participants include dental hygienist teachers, dental hygienists, and dental hygienist students. From the measured results I derive a quantitative index for discriminating different individual skills and for evaluating motion. There are two major contributions to this chapter: (1) I create a measurement system for evaluating the hand-scaling work using IMU and force sensors. (2) I succeed in evaluating the skill of hand scaling based on the measured motion information, by comparing the measured information between dental hygienists and students, the technical differences in skill levels can be clarified.

2.2 Measurement system



Figure 2.1. Hand-scaling work

2.2. Measurement system

2.2.1. System configuration

To evaluate the hand-scaling skill described above, both the scaling force applied on the tooth surface and the motion of the hand scaler should be measured. The hand-scaling work is very delicate. During the hand scaling, the hand motion should not be hindered by the sensors. Therefore, in this research, as shown in Figure 2.2, I connect a force sensor to the tooth from the bottom to measure the scaling force on the tooth surface. In order to measure the hand-scaling motion naturally, as shown in Figure 2.3, I also place a small wireless IMU sensor on the rear end of the handle of the hand scaler.

Hand scaling requires the manipulation of dental instruments and control of force within the limited field of view of the oral cavity so as not to cause unnecessary pain to the patient. Therefore, measuring both force and motion is the key to the successful analysis of hand scaling. This research is novel in that the force of hand scaling was directly measured from the tooth with a six-axis force sensor, and at the same time, the motion of the hand-scaling operation was measured with an IMU. Using an A/D board and Bluetooth communication, the signals from both the force and IMU sensors are measured at 100 Hz.

Measurement of the scaling force

During the training of a dental hygienist student, dental manikins are used. This research used a jaw model (P15HD-500HPRO-S2A1-GSF; Nissin Co., Ltd.). I selected the right mandibular first molar as the target tooth for hand scaling. As shown in Figure 2.2, I place a six-axis force sensor (Mini40 SI-80-4; ATI Industrial Automation Inc.) below the model and connect it with a shaft to one of the roots of the target tooth. To avoid effects from the bone, *i.e.*, the frame of the jaw model, I also set the position of the target tooth a little higher and further away from the frame.

2.2 Measurement system



(b) Structure view

Figure 2.2. Jaw model with a six-axis force sensor under the target tooth



Figure 2.3. Hand scaler equipped with an IMU sensor

Measurement of hand-scaling motion

To measure the hand-scaling motion without affecting the natural hand-scaling motion, I used a light wireless multi-sensor board (Senstick [56, 57, 58]; Matilde Inc.). The IMU sensor in this board can measure the acceleration, angular velocity, and magnetic field simultaneously. In this research, only the acceleration and angular velocity related to the hand-scaling motion are measured. As shown in Figure 2.3, I attach the sensor board to the rear end of the hand scalers (Gracey Curette Original 13/14 #7[Standard]; Hu-Friedy Mfg. Co., LLC.), without inhibiting the natural grasp of the hand scaler. When measuring hand-scaling motions, the IMU can be attached to the hand or arm. However, the IMU is attached to the hand scaler to eliminate confusion about the attachment position due to individual differences such as hand size.

2.3. Experiment

Using the measurement system, I performed an experiment with several participants with different levels of experience in hand-scaling work. The measured data were analyzed and compared based on their levels of experience. The experimental protocol of this research was approved by the research ethics board of Nara Institute of Science and Technology. Before the experiment, informed consent was obtained from the participants.

2.3.1. Setup

Same as in the case of training dental hygienist students, as shown in Figure 2.4, I set the jaw model on an inclined attachment and fixed this to the table. As is the treatment in the dental clinic, the inclination of the model was 60 degrees to make the teeth easily visible to the participants. Figure 2.5 shows the hand-scaling position in the experiment. In this experiment, the participants scale the area of the target tooth indicated by the green arc in Figure 2.5 by using the hand scaler #14 shown in Figure 2.3. The target teeth have projections that mimic tartar. I measured the motion and force in hand scaling of the target tooth until the participants think they have removed the tartar. The measured acceleration, angular velocity, and force data were extracted from when the hand scaler is tooth surface. During the experiment, I also took videos of all participants of the hand and upper body for verification by dental hygienist teachers.

The experiment was conducted with 15 participants, including one dental hygienist teacher, eight dental hygienists, and six dental hygienist students. Table 2.1 shows the work experience of all the dental hygienists. The dental hygienist students were first-year students studying in the same training school, with the same level of learning progress. All dental hygienist students had completed the lecture and training in hand scaling before the experiment. I easily assume that dental hygienists have better skills than students even with their different levels of experience. Before the experiment, I prepared time for participants to practice the use of the device. Considering the level of experience, the practice time was set to 3 minutes for dental hygienists and 10 minutes for dental hygienist students.

2.3 Experiment



Figure 2.4. Experimental setup



Figure 2.5. Target hand-scaling positions

2.3 Experiment

able 2.1 .	Experience a	s dental hygienist of the p	participant
	Experience	Number of participants	
	≤ 5 years	4	
	≤ 10 years	2	
	≤ 15 years	3	

Τa \mathbf{s}

2.3.2. Result

Data acquisition

Figure 2.6 shows the measured data (acceleration, angular velocity, and force) for the dental hygienist teacher.



Figure 2.6. An example of measured data (dental hygienist teacher)

2.3 Experiment

Comparison of the hand-scaling skills

I compared the measured data between the nine dental hygienists and the six students. In this experiment, the operating time and the number of strokes were different for each participant. So as the features of the measured data of the hand-scaling motion, the minimum value, maximum value, and range for each stroke were extracted. The big difference between the dental hygienists and the students was in the maximum values and the range of Z-axis forces. The average maximum scaling force of the dental hygienists (9.08 N) was larger than the students (6.07 N). The average range of the scaling force of the dental hygienists (10.45 N) was also larger than the students (7.18 N). A t-test shows that the dental hygienists exerted more force (p < 0.05).

Figure 2.7 shows the results of the principal component analysis (PCA) [59] with the force of all three axes. The force in the Z-axis, which is the force for lifting the hand scaler up, has a large effect in judging the difference in hand-scaling skill. The second principal component is mainly affected by the value of the X-axis force, which is the force pushing on the tooth.



Figure 2.7. Principal component analysis of maximum force



Figure 2.8. Quadratic discriminant analysis of maximum force peak

Figure 2.8 shows the results of the data classification of all the hand-scaling data using Quadratic Discriminant Analysis (QDA) [60]. There is a clear boundary that can be used to separate the data between the dental hygienists and the students.

2.4. Discussion

Figure 2.6 shows a periodic motion (data in pink boxes) could be measured for each stroke of several millimeters. In one stroke, the hand scaler moves up a few millimeters and the hand scaler rotates slightly. The rotation is to make the tip of the hand scaler follow the curved tooth surface. The measured data showed a clear increase in the X-axis acceleration due to the hand scaling of the curved surface transitioning from the buccal surface to the surface adjacent to
2.4 Discussion

the posterior molar (the acceleration data in the orange boxes). When the tip of the hand scaler returned from the adjacent surface to the buccal surface, the angular velocity of the Y-axis (the angular velocity data in orange boxes) changed significantly. The force in the Z-axis shows the force applied to the target tooth when lifting the hand scaler up. The relatively large Z-axis force (the data in the blue box) occurred when removing the tartar. The other relatively small force occurred when the participant was looking for the dirt.

From the measured movement of the hand scaler and the measured force applied to the tooth, the type of hand-scaling motion being performed by the participants can be characterized.

The dental hygienist students are not good at controlling the motion of the tip of the hand scaler while simultaneously applying pressing and lifting forces to the tooth surface. Figure 2.7 shows that the Z-axis and X-axis force are the most important values for evaluating the hand-scaling skill. Figure 2.8 shows a clear boundary that can be used to separate the data from the dental hygienists and the students. By comparing the skills of all participants with different levels of experience, the results show that it is possible to evaluate hand-scaling skills by using the developed system and the measured data.

Chapter 3

Modeling of contact between hand-scaler blade tip and tooth surface

3.1. Introduction

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.

Therefore, I focused on a function implementable with an actual self-learning simulator that provides feedback on the correctness of students' 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 Figure 1.2 [14]. The tip may damage gingiva when it moves away from the tooth surface [17], and therefore, the use of the middle of

3.1 Introduction

the hand-scaler blade (*hereafter referred to as middle*), as shown in Figure 1.2, 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.

Previous research has included training systems using imaging technologies [44]. 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 Figure 3.1, a camera may not adequately visualize the contact or the absence of contact between the tip and the tooth surface.

3.1 Introduction





(b) By buccal mucosa

(a) By gingiva

Figure 3.1. Example of a concealed hand-scaler blade

The correct motion pattern is created relatively easily because haptic feedbacks 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.

I 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 [61, 62, 63, 64] or by using 3D reconstruction from images [65, 66, 67], both methods have limitations. Pre-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) [44]. Blind spots on cameras have also become a major problem in the implementation phase.

3.2 Materials and methods

Therefore, I considered the use of an inertial measurement unit (IMU) as an alternative approach for contact identification. IMUs can allow recognition and measurement of minute motion. I 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. I 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. I focused on motion because I 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 [41, 42].

I 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, I 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, I 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, I 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, I examined whether the accuracy achieved with both sensors could be maintained while using either sensor alone. I further examined the minimum number of features within one sensor that would maintain an accuracy similar to that obtained with the two-sensor configuration.

3.2. Materials and methods

3.2.1. Hand-scaling simulator

The participants performed hand scaling using the simulator, as shown in Figure 3.2a. The buccal mucosa was removed to observe the blade of the hand

3.2 Materials and methods

scaler during the experiment. The simulator was created based on our previous study [54]. The hand-scaling motion was measured using an IMU (MetaMotion R; MbientLab 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 Figure 3.3. The IMU (Weight including case: 19.5 g) was attached to the end of the gripping portion of the hand scaler, as shown in Figure 3.3a. 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.



(a) Hand-scaling simulator



(b) Target tooth of hand scalingFigure 3.2. Experimental tool



(b) Force sensor

Figure 3.3. Sensor setting

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 Figure 3.3b. I used the data for the three axes of force in this study. A space was created between the target tooth and the model frame to prevent contact between the target tooth (A2A-739-#46; Nissin Dental Products Inc.) and the 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.

3.2.2. Participants

The participants were students in the self-learning practice phase of hand scaling. I 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, I 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.

3.2.3. Hand-scaling task

The participants performed hand scaling on a specific tooth as shown in Figure 3.2b called the *lower right first molar* in the hand-scaling simulator shown in Figure 3.2a. I asked them to perform the task based on the assumption that

3.2 Materials and methods

the tooth had buccal mucosa. They performed seven consecutive hand-scaling strokes as a single task. I 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 Figures 1.1, 1.2, 1.3, and 1.4 [14].



Figure 3.4. Contact between the blade and the tooth surface



Figure 3.5. three-axis of IMU during forearm rotation

3.2.4. Experimental factors

The experimental factor was the contact position of the blade, which was categorized as tip contact or middle contact, as shown in Figure 3.4. 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.

3.2.5. Sensor measurement values

Measurements were acquired from the IMU attached to the hand scaler and the force sensor attached to the target tooth. Measurements of acceleration, angular velocity, and force were acquired for each of the three axes (nine dimensions in total). Table 3.1 shows the correspondence of each axis in the forearm rotation motion (Figure 3.5).

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 fore-
	arm rotation moving in the direction of the tip and
	vertically 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 3.1. Description of sensor measurement values in the forearm rotation motion

3.2.6. Analysis method

Preprocessing

The force, acceleration, and angular velocity data were synchronized using synchronous signals of the trigger motion, as shown in Figure 3.6. 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 Figure 3.6. This preprocessing was performed because the duration from the synchronous signals to the first stroke varied for each participant.



Figure 3.6. Example of synchronization and extraction of the data section for analysis

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 3.2. Each feature was calculated for each trial from the sectional data obtained during preprocessing. I 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, I selected features that reflected the magnitude of motion and scattering of the magnitude.

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
$\overline{7}$	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

Table 3.2. Features values

3.2 Materials and methods

Classification of the contact position of the blade

To identify whether the tip or middle was in the contact with the tooth, I used SVM [68, 69], which can determine an appropriate discriminative boundary even with a small amount of training data. I trained and tested the data separately for each participant to account for differences among participants and verified whether it was possible to 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 randomly divided into 5 parts and standardized as average = 0 and standard deviation = 1. I 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. I analyzed the accuracy value that corresponded to the highest average accuracy. Table 3.3 lists the values of SVM hyperparameter C used in each case.

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

Table 3.3. C parameters

Comparison of classification accuracy

First, I 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 [70].

Furthermore, I 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 Figure 3.7 and below.

- (i) Models with i (i = 1, ..., 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, \cdots , 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 of 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 (IMU+F features) and the average accuracy of N predictors (IMU+F features) and the average accuracy of N predictors (IMU+F features) and the average accuracy of N predictors (features) were equivalent.



Figure 3.7. Definition of i-highest model

3.3. Results

3.3.1. Classification accuracy of the contact position of the blade

The average accuracy of each participant according to the SVM is shown in Figure 3.8. 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 $97.1\pm4.7\%$, $95.9\pm6.9\%$, and $88.8\pm14.2\%$, respectively.









3.3 Results

Table 3.4. 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 3.5. 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

Symbols	Aay Aaz Sax Say Saz Agx Agy Ag		0	
	Aax	0	0	С

Table 3.6. Combinations of two IMU features with no significant difference in classification accuracy in comparison with IMU+F features

3.3.2. 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 3.4. 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).

3.3.3. 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. I show the results of the IMU that was able to examine the minimum combination of features. Figure 3.9 shows the average accuracy of each participant using the IMU+F features and one and two IMU features as predictors. Table 3.5 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 3.6 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 (Aax) was always included in these combinations.

3.4. 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, I considered this approach to have a high potential for clinical application.

3.4 Discussion

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 a 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.

Novices recognize that dirt can be removed by applying force from the handscaler blade to the tooth surface. Therefore, force application is likely to be controlled regardless of how the blade is used. Therefore, it is conceivable that the feature value of motion rather than force influences the classification. Although I consider that the force feature is an important factor when evaluating handscaling motion, I consider that the force feature can be omitted when classifying the contact between the blade and the tooth surface.

To simplify the data processing process, I 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 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 3.6, 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 3.6 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 handscaler 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.

Chapter 4

Modeling of exemplary motion and educational effect

4.1. Introduction

In Chapter 3, a classification model capable of judging hand-scaling motion using two-class SVM was presented based on the values obtained from the proposed measurement system created in this research. This model creates training data from individual hand-scaling motions. For students who have acquired a certain level of hand-scaling motion, it can be used effectively as a function of a selflearning simulator. However, if students use a self-learning simulator, they are beginners in the first stage of training. It is not easy to obtain learning data from beginners for exemplary hand-scaling motions. Beginners are not yet familiar with the motions and do not possess individual motion habits; it would be ideal if there was an improved generalized classification model. Considering that in the educational setting, teachers demonstrate examples and students improve their skills through one-on-one instruction, if there is a model that can be used as a generalized classification model, it is possible to acquire motions that are similar to that model. It is assumed that exemplary motions can be learned.

Therefore, this chapter aims to create an exemplary hand-scaling motion model, and the effects of practicing with feedback for motion classification on beginners are investigated. Modeling exemplary hand-scaling motion is ideal as a model that can be applied to self-learning simulators, and the standardization of education can be achieved. In the experiment, an exemplary hand-scaling motion of a dental hygienist is considered, and the motion is modeled using a one-class SVM. Next, a judgment system for hand-scaling motions using the model has been developed, and participants who are beginners and had no experience in hand scaling have been asked to use the system for practice. Then, to feed back advice based on the measured values, any influence on learning has been analyzed.

4.2. Experimental method

First, the exemplary hand-scaling motion is modeled. After that, participants are divided into groups with and without advice using the motion judgment results obtained from the model and training hand scaling.

4.2.1. Participants

The learning data to create the model were obtained by one dental hygienist with 20 years of work experience. She has experience in teaching at a dental hygiene training school. The practicing participants were adults who had never studied dentistry and were asked to participate in the experiment, divided into two groups: nine participants with advice and eight participants without advice.

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

4.2.2. Hand-scaling task

First, the practicing participants were given a 20-minute lecture on the operation of hand scaling. The lecture comprised an explanation using materials (Appendices A.1 and A.2) and confirmation of the basic operation by actually grasping the hand scaler. Then, they were asked to perform a task in which they had to perform three consecutive strokes. During hand scaling, the participants were asked to grasp the hand scaler similar to the writing-like variant grasping method [14] shown in Figure 1.1 and perform the forearm rotation motion shown in Figure

1.4. The site referred to one point shown in Figure 4.1 on a specific tooth known as the lower right first molar. The data were obtained 100 times from dental hygienists who create training data and 50 times from practicing participants. Practicing participants were presented with the material (Appendix A.3) that could be checked when needed in a timely manner. Practicing participants with advice were informed in advance and asked to confirm the advice after each trial.

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). Each participant used a new hand scaler to ensure the uniformity of the blade sharpness. The target tooth was replaced with a new tooth for each participant because the tooth surface was worn down owing to hand scaling.

One point on the extension of the fissure groove



Figure 4.1. Hand-scaling point

4.2.3. Measurement of hand scaling

The measurement system (Figures 3.2a and 3.3) in the experiments mentioned in Chapter 3 was used to measure hand-scaling motions. However, the camera attached to the hand scaler is removed in this experiment. The same position is used for the sensors. Therefore, the coordinate system of the sensors remains unchanged.

4.2.4. Sensor measurement values

The sensor measurements were obtained from the IMU attached to the hand scaler and force sensor attached to the target tooth (nine-axes). Each axis of the forearm rotation motion (Figure 1.4) is summarized in Table 3.1.

4.2.5. Judgment system based on the modeling of exemplary motions

Figure 4.2 shows the flow of the judgment system and the content of each process.



Figure 4.2. Judgment system flow

Preprocessing

Three consecutive strokes are performed in one hand-scaling task, and the data in the interval from the minimum value after the first stroke to the minimum value after the second stroke of the force data of the Z-axis is extracted from the sensor measurements as the analysis target. This was done to truncate the movement data before and after the task and extract only stable stroke movements.

Feature extraction

The features of the measured values can calculate the average and standard deviation, which represent the magnitude of motion in each of the three axes (force, acceleration, and angular velocity) and variation in magnitude (blurring) as features (18 items) (Table 3.2). However, in the classification model mentioned in Chapter 3, two IMU features with high accuracy are combined (Table 3.6). Therefore, a classification model with two features was first created. The task mentioned in Chapter 3 analyzes 7 strokes of data; however, this experiment was conducted for one stroke. Then, the average values of the acceleration X-axis (Aax) and acceleration Z-axis (Aaz), which are not standard deviation feature values, were considered. Beginners are trained on the motion of the hand scaler and force; in this model, features that can focus on the motion of the forearm rotation are selected. Simplified training reduces the cognitive load on beginners [71]. In addition, as the subject of this experiment is a beginner, providing multiple pieces of advice at the first stage of training may lead to confusion, and it is appropriate to reduce it to two features.

Modeling of exemplary motion

A one-class SVM [72] was used. A model was created using 100 datasets of exemplary hand-scaling motions as training data, 5% of which were set to be outliers. The values of Aax and Aaz were used as predictors; MATLAB R2021b and the Statistics and Machine Learning ToolboxTM (The MathWorks, Inc.), i.e., a MATLAB toolbox, were used for SVM calculations. Parameters were as specified in MATLAB. Data were standardized as average = 0 and standard deviation = 1. The kernel function was specified as a radial basis function. The C and γ parameter of the SVM hyperparameter was set to 1 and $1/KernelScale^2$, respectively. The KernelScale, which divides this entire predictor, used a setting where the appropriate scale factor is selected.

Score and label of SVM classification

The SVM classification score (SVM score) for classifying a measurement is the signed distance from the measurement to the decision boundary. A positive

SVM score indicates that the measure is in the exemplar class. A negative SVM score indicates that the measure is not in the exemplar class. The positive class classification score formula f(x) is the trained SVM classification function.

$$f(x) = \sum_{j=1}^{n} a_j y_j G(x_j, x) + b,$$
(4.1)

where x denotes the feature obtained from the measurement. $(\alpha_1, ..., \alpha_n, b)$ denote the estimated SVM parameters, y_j denotes the label (-1: not in the exemplar class or 1: in the exemplar class), and $G(x_j, x)$ denotes the dot product between x and the support vectors in the predictor space. The negative class classification score is -f(x).

Advice

The feedback method is not considered in this experiment. Advice is given in verbal expressions on the display screen. Figure 4.3 shows the advice display screen. In the lower left side of the screen, the results of the participant data's classification with the exemplary motion model and SVM scores are displayed.



Figure 4.3. Advice display of the judgment system

• Judgment of the hand-scaling motion in the exemplary motion model "Correct motion": when the participant's hand scaling is judged as a model motion.

"Improvement points": when the participant's hand scaling is not judged as a model motion.

SVM score of the exemplary motion model The SVM scores of the current and previous trials are displayed. An SVM score of 0 or higher denotes the model motion. For example, SVM scores of -2.5 and -3.0 in the previous and current trials indicate that the hand-scaling motion is worse than that in the previous trial.

The advice on the lower right side of the screen is as follows: A combination of Aax and Aaz data in the exemplary motion model with reference to the training data is set, and a classification judgment is based on this combination. The maximum and minimum values of exemplary motion with Aax and Aaz are produced. Based on this, the advice that can be displayed by judging Aax and Aaz from the participant's motion measurements is provided.

• Moving width of the tip of the blade indicated by Aax of the feature "The motion width of the tip of the blade is too small. Please extend the tip of the blade to 2-3 mm in width.": when the motion is smaller than Aax of the model motion

"The motion width of the tip of the blade is appropriate.": when Aax is within the range of the model motion

"The motion width of the tip of the blade is too large. Please modify the tip of the blade to a smaller width of 2-3 mm.": when the motion is larger than Aax of the model motion

• Rotation width of the forearm rotation indicated by Aaz of the feature In this judgment, as the relationship between the posture of the hand scaler and contact of the tip of the blade produces an effect, the user needs to check the posture of the hand scaler and contact of the tip of the blade, except for the aptitude case.

"Please check the posture of the hand scaler and contact of the tip of the blade. Did the tip of the blade catch? The rotation range of the forearm rotation is too small. Please increase the rotation width.": when the motion is smaller than Aaz of the model motion

"The rotation width of the forearm rotation motion is appropriate.": when Aaz is within the range of the model motion

"Please check the posture of the hand scaler and contact of the tip of the blade. Did the blade tip slip? The rotation width of the forearm rotation is too large. Please decrease the rotation width.": when the motion is wider than Aaz of the model motion

4.2.6. Analysis

Validation of the model

The dental hygienists who created the training data were asked to subjectively judge the label of a participant's motion as exemplary or not based on the practicing participant's motion that was recorded. The reason for asking the dental hygienists who created the training data to make the judgment was that the dental hygienists themselves had the best understanding of exemplary motions and could use the same criteria in the subjective judgment. However, the exemplary motion model was judged based on Aax and Aaz. The participants were asked to make judgments on the "blade tip travel width" and "forearm rotation width," which can be determined based on Aax and Aaz. 1-10 trial data of 10 randomly selected participants will be used as judgment data. A total of 100 trials of data will be judged and compared with the judgment results of the model and evaluated in terms of accuracy, precision, and recall.

Educational effects

In addition to checking the change in the SVM score, it needs to be checked whether there was any difference in the change in the SVM scores of the groups with and without advice. After calculating the average for every 10 trials, the following values were calculated for each participant representing the difference in the SVM score for every 10-trial interval (change in SVM score) considering the average of 1–10 trials.

(SVMscore average of 11 to 20 trials) - (SVMscore average of 1 to 10 trials) (4.2)

 $(SVMscore\ average\ of\ 21\ to\ 30\ trials) - (SVMscore\ average\ of\ 1\ to\ 10\ trials)$ (4.3)

(SVMscore average of 31 to 40 trials) - (SVMscore average of 1 to 10 trials) (4.4)

 $(SVMscore\ average\ of\ 41\ to\ 50\ trials) - (SVMscore\ average\ of\ 1\ to\ 10\ trials)$ (4.5)

Next, the left-tailed hypothesis test of the Wilcoxon rank sum test was performed for the groups with and without advice. The null hypothesis defines that there is no difference between the groups with and without advice in every 10trial interval minus the 1-10 trial average. The alternative hypothesis is that the group without advice possesses a smaller median than the group with advice with regard to the difference obtained by subtracting the 1-10 trial average from the every 10-trial interval average. In other words, if the alternative hypothesis is accepted with a p-value less than 0.05, I consider that training with advice is better at maintaining or improving its effectiveness than training without advice. Furthermore, the number of training rounds to improve the hand-scaling motion is unknown. Each participant performs the experimental task 50 times and a set of 10 trials is separated and evaluated in the test. Therefore, the Bonferroni correction was applied to the p-values of the test results to consider the issue of the multiplicity of tests.

4.3. Results

4.3.1. Validation of the model

Figure 4.4a shows the confusion matrix between the results of the dental hygienist's subjective judgment of whether the model was an exemplary motion and results of the exemplary motion model's judgment. "Success (Inside)" indicates within the range of the exemplary motion, and "Failure (Outside)" indicates outside the range of the exemplary motion. The accuracy is 74.0%, the precision is 82.5%, and the recall is 63.5%. Figure 4.4b shows a confusion matrix with the exemplary motion model in which outliers are changed to 0% because the recall is low. The accuracy is 73.0%, and the precision is 77.8%, the recall is 67.3%.



Figure 4.4. Confusion matrix of judgments made by the exemplary motion model and dental hygienist

4.3.2. Educational effects

Figure 4.5 shows a graph of the average results of each trial of the groups with and without advice. The SVM score was higher in the group with advice than in the group without advice for 10-30 trials.

Figure 4.6 (Table 4.1) shows the results of the left-tailed hypothesis test of the
Wilcoxon rank sum test comparing the groups with and without advice. A p-value less than 0.05 rejects the null hypothesis and adopts the alternative hypothesis. The p-value with Bonferroni correction of 11-20 trials showed a significant difference.



Figure 4.5. Change in the average SVM score for each trial of the group with and without advices



Figure 4.6. Left-tailed hypothesis test of the Wilcoxon rank sum test comparing groups with and without advices considering the difference in the average SVM scores for 1-10 trials and every 10 trials

Table 4.1. Left-tailed hypothesis test of the Wilcoxon rank sum test comparing groups with and without advices considering the difference in the average SVM scores for 1-10 trials and every 10 trials

The difference in average SVM	p.value	Bonferroni correction
score		for p.value
11-20 trials - 1-10 trials	0.010	0.040
21-30 trials - 1-10 trials	0.084	0.336
31-40 trials - 1-10 trials	0.336	1.344
41-50 trials - 1-10 trials	0.481	1.924

Figure 4.7 shows the evolution of the SVM scores of the participants that reveal the educational effect of advice on 1-50 trials. The SVM scores increased as the number of trials increased. Figure 4.8 shows the relationship between SVM scores and Aax and Aaz plotted simultaneously based on the training and participant data of the exemplary motion model. The contour lines indicate SVM score boundaries. The color of the contour line indicates which SVM score is represented by the color bar on the right of the figure. The higher the number of trials, the higher the SVM score, and an SVM score of 0 or more indicates that the motion is closer to the model motion.

4.3 Results

However, there are significant differences in individual aptitude for training. Figures 4.9 and 4.10 show the results of the participant of the group without advice; the participant performed motions similar to the exemplary motion from the beginning. Figures 4.11 and 4.12 show the results of the participant of the group with advice; this participant exhibited motions significantly different from the motions demonstrated by the model until the end.



Figure 4.7. SVM scores indicating ideal progress



Figure 4.8. Contour plots indicating ideal progress



Figure 4.9. SVM scores similar to the exemplary motion from the beginning



Figure 4.10. Contour plots similar to the exemplary motion from the beginning



Figure 4.11. SVM scores indicating no improvement



Figure 4.12. Contour plots indicating no improvement

4.4. Discussion

In this experiment, the same dental hygienist was asked to obtain training data and judge whether the hand-scaling motions practiced by the participants were exemplary. If this dental hygienist was a teacher, she could create feedback equivalent to the results of her own subjective judgment by creating her own motion model. In addition, when multiple teachers are involved, feedback can be provided based on a unified judgment standard without depending on the judgment of each individual teacher.

The precision was 82.5% in the evaluation of the model for the exemplary motion. The accuracy result was slightly lower than the precision (74.0%). The recall was even lower (63.5%). However, this model has been considered in the experiment because it exhibited a low false negative rate of 14.6% and a low probability of judging non-exemplary motions as equivalent to exemplary motions. This was considered to avoid training other than the exemplary motion as the correct motion. As shown in Figure 4.4, the subjective evaluation of the dental hygienists judged several motions exemplary compared to the model. The subjective evaluation of the dental hygienist includes flexible judgments. It is possible that there are motions that she judged as exemplary that can not be represented in the training data. Therefore, the challenge is to create various exemplary motions that can help improve the accuracy of the model. This issue can be solved by repeating the process of adding practice motions, which were judged as exemplary motions based on subjective evaluation, to the training data. The process will help improve the accuracy of the model.

Furthermore, the model was used in training experiments with outliers set at 0%. Figure 4.4b shows the confusion matrix of the model created with 0% of the outliers. The recall was slightly increased to 67.3%. When teachers create training data, using an appropriate proportion of outliers can help improve and ensure model accuracy, even if the training dataset contains data that deviate from the exemplary motion. When the exemplary motion model is used in actual education, two methods can be used to set the boundary between modeled motions: the creation of training data with wide varieties and the adjustment of the percentage of outliers.

As listed in Table 4.1, the p-value with Bonferroni correction is less than 0.05 for

4.4 Discussion

11-20 trials. It has been confirmed that the SVM scores of the group considering advices are maintained or have improved. Thus, training up to 20 times may have been effective. The participants performed 50 times the experimental task because the number of training rounds to be conducted for one treatment part of the hand-scaling motion was not known. However, long hours of training time are believed to reduce the effectiveness of training equipment [73]. Participants spent ~ 1 h performing the task 50 times. This may cause fatigue and a lack of concentration in the middle of training. In a typical curriculum for dental hygienist education, a one-time class includes training on operating multiple teeth and appropriate breaks. Lectures and practice assignments are structured so that students will not lose their concentration by changing practice teeth. This time there is one type of task, and only limited advice was considered as feedback. The training might have become monotonous, and the effectiveness of training reduced along the way. Therefore, I think that participants can obtain skills effectively if they train in the right number of trials. Figure 4.5 shows a difference in scores between the group with and without advices or 10-30 trials; however, for 30 trials or more, the difference is not that evident. In future studies, it is necessary to consider the appropriate number of trials with reference to the aforementioned results.

Finally, the proposed exemplary motion model demonstrates the possibility of modeling hand-scaling motion that has never been done before. And, it shows the possibility of producing a large educational effect to enable automatic judgment of students' hand-scaling motion.

Chapter 5

Conclusion

This dissertation aims to model the most basic and essential skills related to the contact between the blade of a hand scaler and tooth surfaces based on kinematic and mechanical information and verify the effectiveness of a developed skill-training method based on the evaluation of an exemplary motion model.

5.1. Summary

In Chapter 2, a measurement system for hand-scaling skills was proposed, and it was confirmed that these skills can be evaluated using the measured data. The proposed measurement system comprises two sensors: a six-axis force sensor attached to a target tooth in a jaw model to measure the scaling forces and an IMU sensor attached to a hand scaler to measure hand-scaling motion. In the experiment, the hand-scaling motions of 15 participants with different levels of hand-scaling experience, including one dental hygienist teacher, eight dental hygienists, and six dental hygienist students, were measured. The results indicated that it is possible to measure the hand-scaling force and motion and evaluate individual skills based on the measured values.

Chapter 3 verified whether the features acquired from the IMU attached to the hand scaler and force sensor attached to the target tooth can be used to identify the contact between the tip of the hand-scaler blade and tooth. Data were obtained during hand scaling with forearm rotation. The SVM was used to

5.2 Contributions

classify whether the tip or the middle part of the hand-scaler blade was in contact with the tooth during hand scaling using two types of sensor data. The results confirmed that classification with an accuracy of 97.1% was possible.

Chapter 4 described the creation of an exemplary hand-scaling motion model to judge the motion of a beginner practicing hand scaling. The precision value of the exemplary motion model was 82.5%. Moreover, this model was used to examine the effects of training with feedback for motion classification. Compared with the subjective evaluation by the dental hygienist, the model confirmed high performance in judging whether the hand-scaling motion was model motion. As a result of the training experiment using the advice that can be understood from the model with regard to effectiveness, training using the proposed model was suggested.

5.2. Contributions

The main contributions of this study are as follows:

- A measurement system based on hand-scaling motions for quantitative data was created. The IMU was attached to the handle of the hand scaler to measure the motion of the hand scaler. The force sensor was attached to the tooth to be hand-scaled to measure the hand-scaling force on the tooth.
- Two models have created the model of contact between the hand-scaler blade and the tooth and the exemplary motion model. The measurements obtained from the IMU and force sensor were used, considering the training phase for the first time. The model to identify the contact between the hand-scaler blade and the teeth was created based on the characteristics of an individual, as there was an established behavior for novices. For the exemplary motion, a motion model developed by a dental hygienist was considered for beginners.
- The results of the training experiment confirmed that the exemplary motion model can be effective in education. The model can verify whether the motion is exemplary. The participants were divided into two groups: one with advices and one without advices they were asked to practice hand

5.3 Future work

scaling repeatedly. The comparison of the two groups indicated that the hand-scaling motion of the group with advice was maintained or improved. In addition, to confirm the effectiveness of the model, a comparison was made with the judgments of the dental hygienists. The model was able to make decisions with a high degree of accuracy.

• The main contributions of this study were to create a model that considers differences of the training phase and the actual creation of such a model. The models can be used in two stages: one is to practice approaching the exemplary motion, and the other is to learn the appropriate motion based on the characteristics of an individual.

The contribution of the modeling of hand-scaling motions considering the training phase was achieved. The modeling of instrumental manipulation in dentistry and its potential application to evaluation and training can be expanded to other dental education domains. My recommendation would be to construct a standardized educational system based on the modeling of dental care motions. This system will enable the efficient training of dental health care professionals and contribute to the availability of excellent dental health care professionals.

5.3. Future work

A limitation of this study is that the participants in the experiment performed hand scaling 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 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. In addition, non-verbal instructions made by teachers are required to be analyzed, and feedback methods need to be considered. Feedback based on visual information and haptic technology is highly effective for learning motion.

In this study, a measurement system and two models were proposed. The models can be used as easy-to-use self-learning simulators. However, the proposed model does not enable the comprehensive judgment of a wide range of technical

5.4 Outlook

points of hand scaling. Future studies should further model motions according to technical points, e.g., hand-scaling force, which helps in dirt removal.

5.4. Outlook

This study will help enhance technical education in dentistry. The following problems arise in conventional technical education that relies on the skills of teachers: Technical instruction includes characteristics that teachers themselves are unaware of. The content of instruction changes as the teacher changes. When teaching technology becomes difficult to verbalize, it is not possible for students to understand information given at a time. Modeling motion can help solve the aforementioned problems. By generalizing the motion of multiple teachers while creating a model, the characteristics of individual instructors can be eliminated. In addition, the standardization of instructional content can be achieved using the same model. For techniques that cannot be verbalized, students take time to organize their knowledge, as nuances in the way the techniques are described change as teachers repeatedly teach them. Therefore, using a model to determine correctness and incorrectness and enhancing training while receiving feedback on how to improve motion, students can proceed with training while noticing and understanding information that they are not aware of. As the instruction of the model is based on objective data, judgment, and feedback are uniform. Another advantage is that the training does not confuse students whose knowledge and skills have not matured. Technology education that uses the proposed model can help reduce teacher dependence and burden and help efficiently teach students.

With regard to social implementation, the model can be incorporated into a training simulator to disseminate it in educational settings. The training simulator can be used by students at the same time for practical training. However, the high cost, inability to provide one simulator per student and the large size of the simulator hinder the widespread use of the model. The two models described in this study can be used with an inexpensive IMU and personal computer. With regard to the aforementioned issues, the models meet the challenges of dissemination and have the potential to enhance technical education.

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Publication List

Journals (refereed)

 <u>Tomoko Yui</u>, Sung-Gwi Cho, Yuki Sato, Yasuaki Orita, Ming Ding, Jun Takamatsu, Takahiro Wada and Tsukasa Ogasawara: "Evaluation of Hand-Scaling Skills of Dental Hygienist Students: Identification of Contact Between Hand-Scaler Blade Tip and Tooth Surface," IEEE Access, vol. 10, pp. 120640-120649, 2022. (corresponds to Chapter 3)

International Conferences (refereed)

 <u>Tomoko Yui</u>, Tomoki Ishikura, Sung-Gwi Cho, Ming Ding, Jun Takamatsu, and Tsukasa Ogasawara: "A Quantitative Measurement of Hand Scaling Motion for Dental Hygienist Training," The Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC2020), pp.6040-6043, Submission No.1928, Montreal, Canada, July, 2020. (corresponds to Chapter 2)

Domestic Conferences (in Japanese)

 由井 朋子, 趙 崇貴, 佐藤 勇起, 高松 淳, 和田 隆広, 小笠原 司: "ハンド スケーリングの動作評価を目的とした歯と器具の接触関係が動作に与える 影響の分析", 第22回 計測自動制御学会システムインテグレーション部門 講演会(SI2021), 2C5-02, オンライン, 12月, 2021.

Appendix

A. The lecture material of hand scaling

The materials used in the experiment of Chapter 4 are the following.

A.1. Prior lecture material

























A.2. Handouts that can be checked during the experiment















ハンドスケーラー操作 側方圧 <u>側方圧</u> カリカリと音が鳴り、表面が削れる程度の力を均一にかける 歯の表面に垂直に刃部を押し当てる力 側方圧の向き 23

A.3. Advice display explanation for participants with advice

両面の翌日	 海羽回数
画面の読め	Participant code 100 練習回数: 1
Result 動作の判定 判定は良い場合「適正な動作です」 悪い場合「改善ポイントあり」 ユコア(動作の正しさの目安) 1つ前の動作と今回の動作のスコア 正の整数0以上が目標値 例 前回値 -2.50 今回-3.00 前回より悪い動作になっている	Load_sensor_data → Data_clip → Decision Result Advice 刀部先端の移動機が大きいです。 改直ポイントあり Advice Score 前回: -2.50 → 今回: -3.00 (目標値 OULE) 前期回転運動の回転機は適切
	<u>改善ポイントのアドバイス</u> 次のスライド参照
アドバイスの説明 ^{刃部先端の移動幅のアドバイス31}	 重 <u>類</u>
アドバイスの説明 <u> アドバイスの説明</u> <u> 刃部先端の移動幅のアドバイス3</u> ① 刃部先端の移動幅が小さいです。 ② 刃部先端の移動幅は適切 ③ 刃部先端の移動幅が大きいです。	<u>種類</u> 。幅2-3mmを目指して大きく移動させて下さい。 。幅2-3mmを目指して小さく移動させて下さい。

