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Intelligent dental training simulator with objective skill assessment and feedback

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ABSTRACT

Objective: We present a dental training simulator that provides a virtual reality (VR) environment with haptic feedback for dental students to practice dental surgical skills in the context of a crown preparation procedure. The simulator addresses challenges in traditional training such as the subjective nature of surgical skill assessment and the limited availability of expert supervision.
Methods and materials: We identified important features for characterizing the quality of a procedure based on interviews with experienced dentists. The features are patterns combining tool position, tool orientation, and applied force. The simulator monitors these features during the procedure, objectively assesses the quality of the performed procedure using hidden Markov models (HMMs), and provides objective feedback on the user's performance in each stage of the procedure. We recruited five dental students and five experienced dentists to evaluate the accuracy of our skill assessment method and the quality of the system's generated feedback.
Results: The experimental results show that HMMs with selected features can correctly classify all test sequences into novice and expert categories. The evaluation also indicates a high acceptance rate from experts for the system's generated feedback.
Conclusion: In this work, we introduce our VR dental training simulator and describe a mechanism for providing objective skill assessment and feedback. The HMM is demonstrated as an effective tool for classifying a particular operator as novice-level or expert-level. The simulator can generate tutoring feedback with quality comparable to the feedback provided by human tutors.

1. Introduction

Dental students devote years to the acquisition of sufficient psychomotor skills to prepare for entry-level dental practice. Traditionally, they obtain their dental skills training using plastic or extracted teeth placed on a dental phantom head or live patients under the supervision of dental experts. After a training session, dental experts assess students' dental outcomes based on subjective measures. However, the limitations of this approach include a lack of challenging real-world cases, limited availability of expert supervision, and the subjective manner of surgical skill assessment. With the growth of computer hardware and recent advances in virtual reality (VR) technology, VR simulators for complex procedures such as dental surgery have been introduced [1,2]. The advantages of these simulators are that the students are able to practice procedures anywhere as many times as they want at no incremental cost and that any kind of dental surgical case can be generated. The introduction of haptic devices that provide tactile sensation to users has increased the realism of dental simulators to a great extent [3–6].

Effective surgical skill assessment is important in successfully guiding the novice student to competence [7]. Traditional skill assessment is usually conducted by having an expert surgeon observe the procedure or only the final outcome. However, the level of detail of human expert assessment is limited. With VR simulators, many aspects such as data about the environment and the user's precise actions can be recorded during the simulation and analyzed further to provide fine-grained objective assessment and feedback. Unfortunately, existing dental simulators do not provide this functionality. However, there has been some related work in other fields. Rosen et al. [8,9] present a technique for objective evaluation of laparoscopic surgical skills using hidden Markov models (HMMs). The models are based on force/torque information obtained from a surgical robot. Lin et al. [10] collected various measurements from the da Vinci surgical robot while an operator performed a suturing task. The aim of their study was to automatically detect and segment surgical gestures, which is a part of their ongoing research on automatic skill evaluation. As the da Vinci surgical robot does not provide haptic feedback, their research did not consider force applied during the operation. Mackel et al. [11,12]

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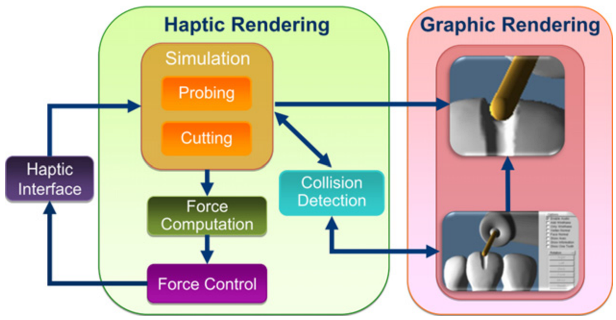

Fig. 1. Simulator system architecture. A 1000 Hz haptic rendering thread coordinates with a 30 Hz graphics rendering thread to update a 3D surface mesh.

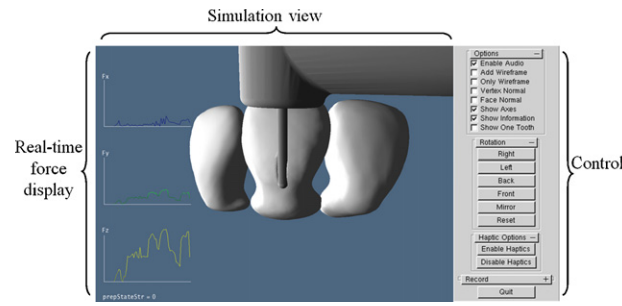

Fig. 2. Graphical user interface of our VR crown preparation simulator.

collected data from five active contact force sensors distributed in the E-Pelvis physical simulator and developed a methodology to evaluate clinical competence of physicians. Sewell et al. [13,14] presented various metrics for automated evaluation of surgical competency in the context of mastoidectomy simulation.

Assessment alone tells students very little about how to improve their performance. Students, especially novices, are dependent on instructors to supervise and provide feedback [7]. To add more educational value, simulators should be able to provide objective feedback to users in order to reduce the time and effort required for instructors to supervise and tutor trainees using the system. Thus, incorporation of strategies for generating objective feedback with quality comparable to that of human tutors is essential to the development of an efficient, intelligent training simulator.

In this paper, we describe a virtual reality dental training system combining realistic haptic feedback with objective dental performance assessment and novel feedback generation mechanisms. While the system currently only simulates crown preparation procedures, many of the techniques and strategies we have developed should generalize well to other medical and dental procedures.

2. Haptic VR crown preparation simulator

We have developed a VR simulator with haptic feedback allowing dental students to practice dental surgical skill in the context of a crown preparation procedure. Crown preparation is the first step in dental restoration with a crown. It is followed by making a dental impression and fabricating the crown. Crown preparation involves cutting the tooth with dental burrs to make space for the planned restorative materials.

We use a PHANToM Omni haptic device (SensAble Technologies Inc.) that allows six degrees of freedom for position sensing and generates three degrees of freedom for force feedback. The virtual dental handpiece is locked to the position and orientation of the haptic stylus. We developed the simulator software using OpenHaptics SDK 2.0 (Haptic Device API) [15] and Optimized Collision Detection (OPCODE) [16].

The simulation system is composed of several components as illustrated in Fig. 1. The simulator contains two separate loops (threads), namely the haptic loop and the graphics loop, running at different frequencies. The graphics loop runs at 30 Hz while the haptic loop runs at a minimum frequency of 1 kHz to ensure a force feedback latency of 1 ms. We use a surface model to graphically represent teeth and the tool. Collision detection and the tooth cutting simulation run within the haptic loop. This is possible due to the OPCODE fast collision detection library and the computational efficiency of the surface displacement algorithm. Fig. 2 illustrates the graphical user interface of our simulator. In this study, the system simulates only labial and incisal preparations, as shown in Fig. 3, in order to avoid conflating tool skills with indirect vision skills requiring a dental mirror. In a previous work [17], we describe the detailed development of the simulator and report on an evaluation of the crown preparation simulator with dental students and experts in which the simulator's realism was rated as acceptable.

In this study, we test the ability of the simulator to produce outcomes that reflect operator skill. Ten simulated partial crown preparation outcomes completed by five students and five experienced dentists were shown to another expert who was not involved in the experiment to assign outcome scores based on errors found in the incisal, labial-incisal, labial-gingival, and marginal regions of the tooth. Examples of simulated crown preparation outcomes are shown in Fig. 4. The maximum outcome score was 16. Fig. 5 shows that the experts' mean score (14.4) was significantly different from the novices' mean score (8.4; $p < 0.05$). This result indicates that the simulator captures the important aspects of the differences between novices and experts.

3. Objective assessment of dental surgical skills

Traditional methods for evaluating surgical performance and skill acquisition during training are limited to measurement of task completion time and number of errors, or a subjective outcome evaluation by an expert [18]. The aforementioned measures do not characterize the operator's movements (e.g., position, orientation, or speed) during the steps required to achieve the desired outcome. The operator who has more accurate movements may take more time to complete a procedure. This speed–accuracy tradeoff is a well-known phenomenon in motor control [19]. Therefore, additional objective measures are needed to quantify surgical performance improvements and assess surgical expertise.

An important advantage of VR simulators is that data about the environment and the user's actions may be recorded. This provides an opportunity to develop an objective method to fairly evaluate a student's performance. Based on interviews with experienced dentists, we hypothesized that among the important features for distinguishing experts from novices in dental surgery are tool movement (position and orientation of the tool over time) and the level of force applied during a procedure. We visualize these features by plotting tool movement of an expert and a novice in three dimensions in Fig. 6 and the average magnitude of the force applied by an expert and a novice over time in Fig. 7.

The difference between expert and novice performance in tool movement can be clearly seen in Figs. 6 and 7. In Fig. 6 we see that the expert's movement is more consistent throughout the operation. In Fig. 7 we see that the force used at each stage of the procedure by experts and novices is also different. The force applied by the expert varies at each stage of crown preparation and is generally greater than the force applied by the novice, which is more uniform. This information suggests that tool movement patterns and force feedback from the haptic device might be valuable in distinguishing experts from novices.

We propose the HMM as a statistical tool to objectively assess surgical performance based on the measured data about the oper-

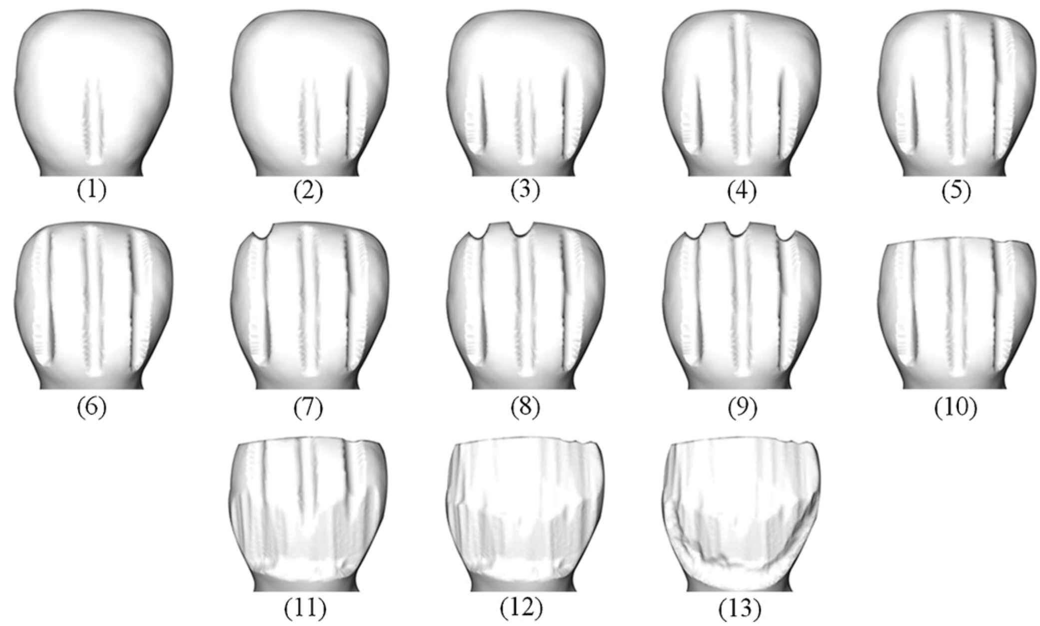

Fig. 3. Thirteen stages of crown preparation on the labial and incisal surfaces of a tooth. Stage (1): labial gingival guiding (central). Stage (2): labial gingival guiding (mesial). Stage (3): labial gingival guiding (distal). Stage (4): labial incisal guiding (central). Stage (5): labial incisal guiding (mesial). Stage (6): labial incisal guiding (distal). Stage (7): incisal guiding (distal). Stage (8): incisal guiding (central). Stage (9): incisal guiding (mesial). Stage (10): incisal reduction. Stage (11): labial reduction (gingival). Stage (12): labial reduction (incisal). Stage (13): labial cervical margin.

ator's actions. HMMs have been used extensively and shown to be effective in applications such as gesture recognition [20] and speech recognition [21]. They also have been used for modeling human operator skills and transferring them to robots [22]. Recently, HMMs have been applied to model complex tasks such as surgery, specifically in automatic assessment of surgical performance in laparoscopy [8,9], pelvic examination [11,12], and mastoidectomy [13,14]. These applications suggest that HMMs have high potential to provide accurate models for assessing dental surgical expertise.

3.1. Experiment

We conducted an experiment to test the ability of a machine learning technique, the HMM, to recognize and classify an observed procedure as novice or expert, based on a set of recorded important features.

We recruited five novices (fourth-year dental students, aged 20–22 years) and five experts (aged 35–45 years) from the Faculty of Dentistry of Thammasat University to participate in the study. All participants were known to the researchers. All of the novices had experience using dental handpieces in cavity preparation from an operative preclinical course but no prior experience performing crown preparation. All of the experts had professional training and experience in prosthodontics. All participants were right-handed. None of the participants had previously received any skill training using a haptic virtual reality system. All participants rated themselves as good or excellent computer users.

The task was to perform crown preparation on the upper left central incisor with the simulator. All participants were instructed to follow the 13-stage process (see Fig. 3) taught to novice students at Thammasat University. We verified that each participant performed all 13 stages in the correct order. Each participant performed five trials of the task. The last trial was used for data analysis.

Our simulator monitors and records all of the data relevant to a user's activity while he/she performs the simulated crown preparation. The data include all of the important features mentioned previously as well as the active status of the drill and the indices of the vertices being cut on the tooth surface. We manually labeled the

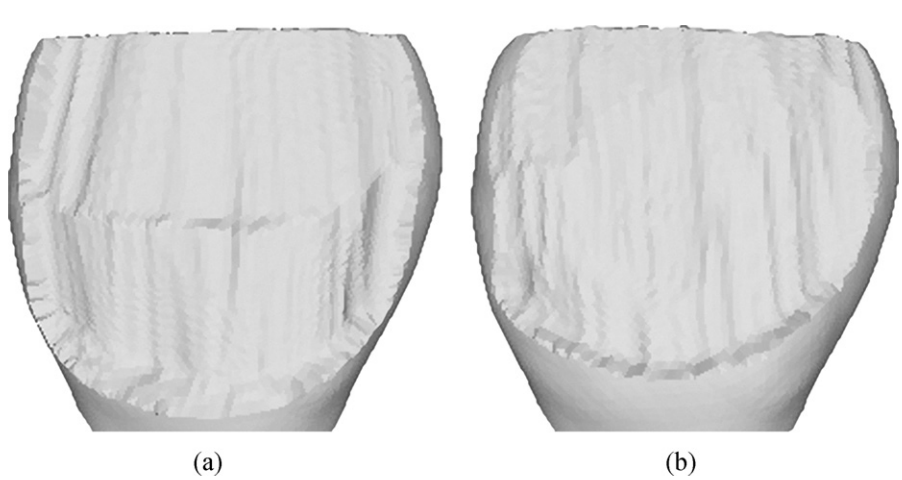

Fig. 4. Example of two outcomes of crown preparation on the labial and incisal surfaces. (a) An expert outcome. (b) A novice outcome. The novice outcome contains preparation errors on labial surfaces.

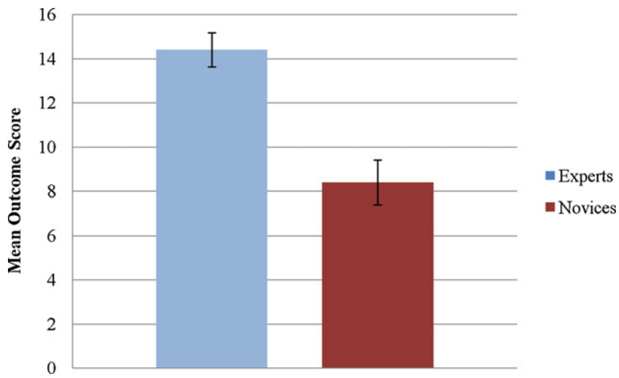

Fig. 5. Mean outcome scores together with 95% confidence intervals for simulated crown preparation performed by experts (mean = 14.4, SD = 0.89) and novices (mean = 8.4, SD = 1.14).

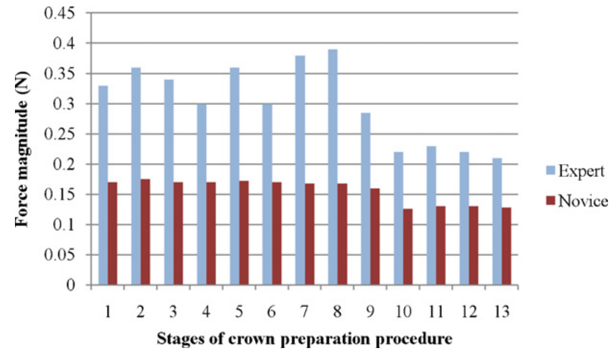

Fig. 7. Example of average force applied by an expert and a novice during 13 stages of simulated crown preparation. Experts tend to use more force with more variation across the stages.

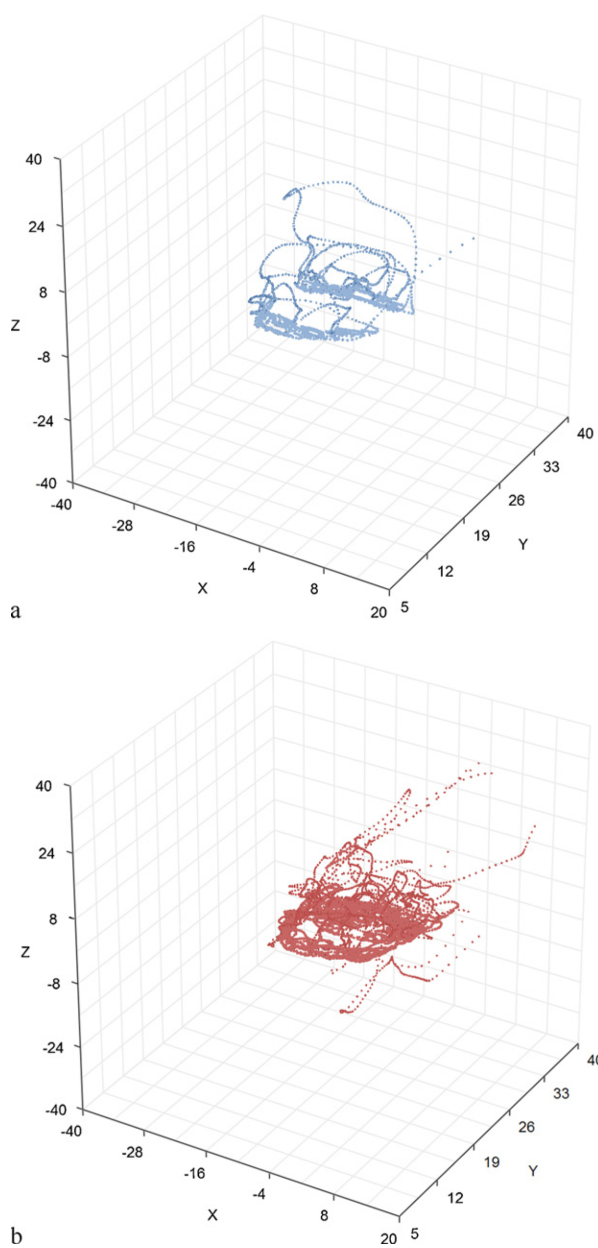

Fig. 6. Example tool paths of an expert (a) and a novice (b). Expert movement is more consistent throughout the operation.

preparation stage transitions in order to facilitate later evaluation of automatic stage segmentation strategies.

After collecting the data from all participants, we built separate discrete linear HMMs to model novice and expert procedure sequences. In our model, the hidden states are the thirteen stages of partial crown preparation. The observed feature set includes the applied force recorded during the simulation as well as the positions and orientations of the dental tool. The manual labeling of preparation stage was *not* used in training or testing. The models were free to assign sequence elements to any of the hidden states as required to model the data. We normalized each feature element to the same range by z-scaling. Since we use discrete HMMs, we first converted the feature vectors into symbols using the k-means clustering algorithm. As each of the thirteen stages in crown preparation has a distinct force and movement pattern, we chose $k = 13$. We trained the novice and expert HMMs by adjusting the model parameters to maximize the probability of the training sequences. After training, we calculated the probability and log likelihood of the test sequences under the novice and expert HMMs using the forward algorithm [21] to find the model that best describes the test sequence data. When the log likelihood of a test sequence under the novice HMM is greater than that under the expert HMM, the system classifies the test sequence as a novice sequence; otherwise, the system classifies it as an expert sequence.

3.2. Results

We performed five-fold cross validation. We used a different k-means for every cross validation fold and the same k-means for the novice and expert model in the same fold. For each fold, we trained the novice HMM with four novice and four expert sequences. To determine the accuracy of the method, after training the two HMMs in each fold, we fed the test novice and expert data to each model.

The average log likelihood of all sequences across all five folds for the two HMMs is shown in Table 1. In every cross validation fold, the log likelihood of every test sequence under its corresponding HMM was higher than that under the other HMM. These results demonstrate the ability of the HMM to distinguish between novice and expert performance with 100% accuracy. However, we do note that the number of participants (10) was relatively small.

Table 1
Average log likelihood results for expert and novice performance sequences.

	Log likelihood for expert HMM	Log likelihood for novice HMM
Expert performance	-3.574×10^3	-2.229×10^6
Novice performance	-6.272×10^5	-3.494×10^3

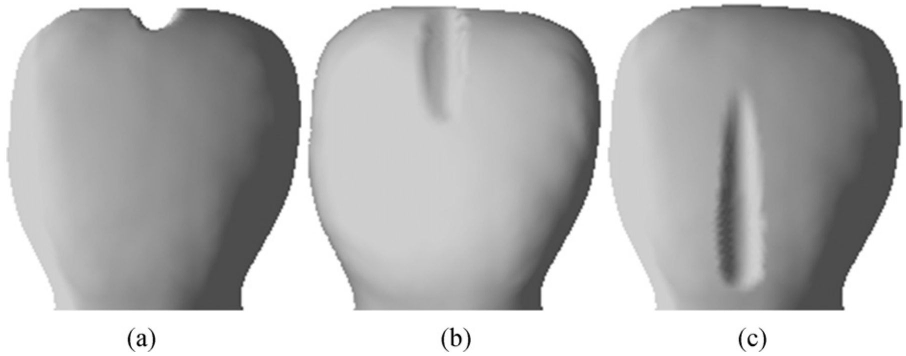

Fig. 8. Examples of crown preparation stages. (a) Stage (1): mid-incisal depth cut. (b) Stage (5): mid-upper-labial depth cut. (c) Stage (9): mid-lower-labial depth cut.

4. Strategies for objective feedback generation

The stage of the crown preparation procedure and its unique force/position/orientation characteristics are the basis of our feedback generation mechanism. The average position, orientation, force, and main axis of force direction differ between the procedure stages. In stage (1) (Fig. 8), for example, force and tool movement is mostly in the minus *Y* direction, while in stage (5) (Fig. 8), force and tool movement progress mostly in the minus *Z* direction. These characteristics can be observed by the simulator and compared to a gold standard in order to generate useful feedback. Examples of our feedback strategy considering applied force for stages (1) and (5) are shown in Table 2.

We generate feedback for position and orientation using the same strategy. For example, Fig. 9 shows a stage in which a novice's tool orientation was very different from that of experts. In this case the feedback generated was "try to lower the degree of rotation around the *X* axis." For states in which the operator does well, we generate a compliment such as "well done."

4.1. Experiment

The main objective of this experiment was to test the overall acceptability of the training feedback generated by the simulator.

The simulator loaded the log files of all five novices collected during the previous experiment described in Section 3.1 and replayed the procedure, one novice at a time. During playback, the system used the manually specified stage labels to segment each sequence into the 13 stages of the preparation procedure. The system observed the characteristics of each stage, computed statistical results, compared them with the statistics acquired from experts, and then generated and displayed the tutoring feedback messages on the screen. An expert examined both a replay of the novice procedures and the feedback generated by the system. The corresponding force values along three axes were also plotted on the screen during replay to aid understanding of how the forces were applied by the operator.

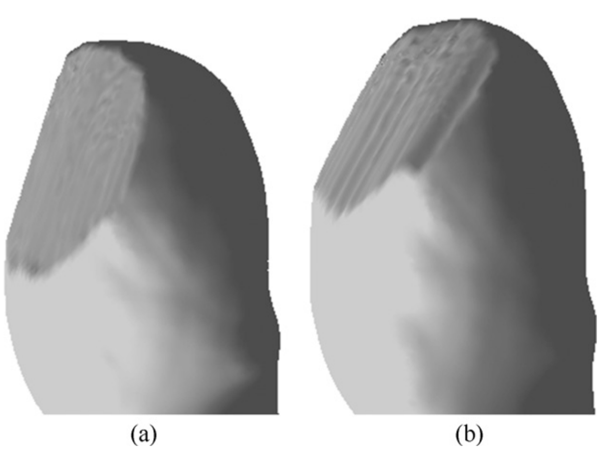

Fig. 9. Example of a difference in tool orientation between (a) expert and (b) novice.

During the experiment, a total of 65 tutoring feedback messages were generated. The expert was asked to rate the acceptability of each feedback message on a scale of 1–5, where 1 implied unacceptable, 2 implied not quite acceptable, 3 implied not sure, 4 implied close to acceptable and 5 implied acceptable.

4.2. Results

The reader may refer to Fig. 8 for the desired outcomes of stages (1), (5) and (9).

Table 3 shows some of the expert's evaluation of the system's feedback messages. During stage (5), during which the main force should be applied in the minus *Z* direction, the average force applied by a user in this direction was not within one standard deviation of the expert mean (the acceptable range was 0.184–0.290 N). Since the novice's average force was around half that of the expert, the generated feedback, "Force in minus *Z* direction should be 2 times higher," was rated as acceptable (score 5).

For stage (9), however, even though the situation in minus *Z* direction was almost the same as in stage (5), the feedback ("Force in minus *Z* direction should be 2 times higher") was rated as not sure (score 3). The expert noticed that, during this stage, the force value in *X* and *Y* was quite high although they should have been close to zero. There might be two causes for this behavior; either the novice did not know the main direction of the force in this stage (minus *Z*) or he/she knew but could not control the tool to move in the right direction. The expert suggested giving a tutoring hint such as "Do you know that minus *Z* should be the main direction of force in this stage?" This kind of hint would be especially useful in online training as the system can observe a novice's reaction after the feedback is given. Note that even though we have not yet applied this strategy, the system was capable of detecting the behavior as the forces in the *X* and *Y* directions (0.108 N and 0.115 N, respectively) were both more than one standard deviation from the expert means.

For stage (1), the generated feedback, "Force in minus *Y* direction should be 3 times higher," was ranked as close to acceptable (score 4). The expert commented that a novice could accidentally damage a tooth in this stage if he/she tried to applied too much force; therefore, she suggested that the feedback could possibly be only "2 times higher" rather than "3 times higher".

The distribution acceptability ratings for all 65 training feedback messages generated by the system are shown in Table 4. The aver-

Table 2
Examples of feedback generated in stages (1) and (5) considering only applied force. Subscript *e* indicates the expert average value (out of five experts) with one standard deviation while *n* indicates the current novice value. The full table considers every feature (force, position, and orientation) and covers all 13 stages for each novice.

Stage	F_x (N)	F_y (N)	F_z (N)	Feedback
1_e	0.103 ± 0.037	0.480 ± 0.047	0.106 ± 0.023	*"Force in minus Y direction should be 3 times higher"*
1_n	0.026	0.164	0.091	
5_e	0.040 ± 0.014	0.038 ± 0.019	0.237 ± 0.053	*"Force in minus Z direction should be 2 times higher"*
5_n	0.028	0.019	0.129	

Table 3
Part of the expert evaluation form for stages (1), (5) and (9). Subscript *e* indicates the expert average value (out of five experts) with one standard deviation while *n* indicates the current novice value. The full evaluation form contains all 65 cases and shows all features (force, position, and orientation) considered in the feedback generation mechanism.

Stage	F_x (N)	F_y (N)	F_z (N)	Feedback	Acceptability
1_e	0.103 ± 0.037	0.480 ± 0.047	0.106 ± 0.023	*"Force in minus Y direction should be 3 times higher"*	4
1_n	0.026	0.164	0.091		
5_e	0.040 ± 0.014	0.038 ± 0.019	0.237 ± 0.053	*"Force in minus Z direction should be 2 times higher"*	5
5_n	0.028	0.019	0.129		
9_e	0.064 ± 0.024	0.035 ± 0.019	0.285 ± 0.033	*"Force in minus Z direction should be 2 times higher"*	3
9_n	0.108	0.115	0.159		

age score assigned by the expert for the generated feedback was 4.154 out of 5.

5. Discussion and conclusion

In this paper, we introduce our VR dental training simulator and describe a mechanism for providing objective skill assessment and tutoring feedback. After a procedure is done, the simulator is able to classify the performance of a particular operator as novice-level or expert-level based on the force applied, tool position, and tool orientation using a HMM. Moreover, the simulator can later generate tutoring feedback with quality comparable to the feedback provided by human tutors. The evaluation results are promising and prove the applicability of the simulator as a supplemental training and performance assessment tool for dental surgical skills.

The accuracy of our automatic performance assessment system using HMMs is high. The system can correctly classify the categories of all the test sequences. However, the number of participants in our study was relatively small and most had similar levels of expertise within their categories which might introduce bias. In this study, we assumed and verified that each participant followed all stages in the correct order; therefore, errors involving deletion or insertion of stages are not considered. Experiments with more participants and various skills levels will be conducted in future work.

Simulation technology is increasingly being used to improve healthcare education. Specifically, virtual reality technology allows for more advanced simulation improving upon the state of the art in dental simulation. Our haptic virtual reality simulator allows users to practice crown preparation in the presence of visual and tactile feedback. In this study, all process-related data (e.g., force used, position and orientation of the dental tool) is readily available for recording by the simulation software. This could be difficult to achieve in a traditional training environment. Based on the recorded data, our system objectively assesses the performance and provides tutoring feedback without the presence of a human expert. This is the novel aspect of our work.

Table 4
Distribution of feedback acceptability ratings for 65 generated feedback messages. The average score was 4.154.

	Feedback acceptability ratings				
	5	4	3	2	1
Frequency	23	32	7	3	0

Our dental training simulator presented here simulates crown preparation only. Other complex dental operations involve complicated factors such as cutting through different layers of a tooth, which have different tissue properties, and the need for other dental tools beside a dental drill. The system presented in this paper would have some difficulty simulating operations that involve different tissue types with the surface representation and displacement algorithm. We are currently implementing a volumetric approach to represent the tooth and a robust cutting simulation technique that works well with volumetric data. We recently added a virtual dental mirror which allows students to practice indirect vision skills. The screenshot of the current prototype is shown in Fig. 10.

Our system uses the manually specified stage labels to generate tutoring feedback messages for each stage. Strategies for automatic stage segmentation will be investigated in future work. The training feedback generated by the simulator generally agrees with an instructor. However, novices are sometimes unable to judge their own effort during the operation. For this reason, providing only verbal feedback on applied force such as "*. . .force should be 2 times higher. . .*" might be insufficient in guiding novices how to improve their performance. Automatically moving the haptic stylus in the student's hand along the recorded expert path will not solve the problem as it is a passive method and students still cannot learn the actual forces applied by the expert.

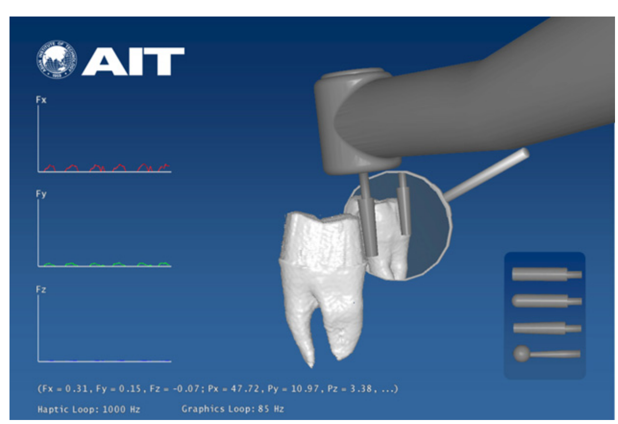

Fig. 10. Screenshot acquired from the current simulator prototype based on a volumetric approach.

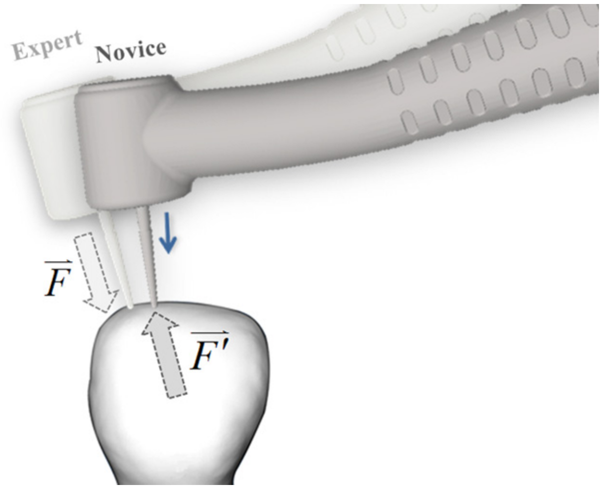

Fig. 11. Path and force learning with visual and haptic information.

To overcome this problem, we are investigating a method proposed by Saga et al. [23,24]. They present a haptic teaching technique to teach hand skills tasks such as calligraphy by rendering the force applied by the expert on the haptic device but rendering it in the opposite direction. A student holding the haptic device must then apply the same amount of force in the original direction to cancel out the rendered opposite force to proceed with the operation.

Fig. 11 illustrates the idea of our implementation of this method. In the figure, the expert's tool movement is played back and a student tries to learn the path by following the movement of the expert's tool. Since the expert was pressing the tooth surface with force $\overrightarrow{F}$, the force $\overrightarrow{F'}$ with the same magnitude but opposite direction is rendered to the novice's stylus, pushing it away from the correct path. In order to keep up with the expert's movement as well as to stay on track, the novice has to apply force $\overrightarrow{F}$, to cancel out the force $\overrightarrow{F'}$. With this technique, both the visual and haptic information from the expert's session can be transferred to the novice in a proactive manner.

More complex procedures might involve complicated pathways such as circular motion. Moreover, advanced students might perform a procedure in a different direction or omit some procedure stages. While the path and force learning discussed earlier might be able to handle the complex procedures, we will certainly need more sophisticated reasoning as we move to more challenging tutoring scenarios with more advanced students.

We will continue working on enhancing the realism of the simulator as well as exploring additional tutoring strategies. We will also investigate a technique to automatically segment procedure stages to replace the current manual labeling. Finally, we are conducting other research where we only consider the outcome of a procedure rather than the steps needed to get to the outcome.

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