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Recognizing Clinical Styles in a Dental Surgery Simulator

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Abstract

Recognizing clinical style is essential for generating intelligent guidance in virtual reality simulators for dental skill acquisition. The aim of this study was to determine the potential of Dynamic Time Warping (DTW) in matching novices' tooth cutting sequences with those of experts. Forty dental students and four expert dentists were enrolled to perform access opening to the root canals with a simulator. Four experts performed in manners that differed widely in the tooth preparation sequence. Forty students were randomly allocated into four groups and were trained following each expert. DTW was performed between each student's sequence and all the expert sequences to determine the best match. Overall, the accuracy of the matching was high (95%). The current results suggest that the DTW is a useful technique to find the best matching expert for a student so that feedback based on that expert's performance can be given to the novice in clinical skill training.

Keywords:

Automated procedure assessment; Dynamic time warping; Virtual reality; Haptics; Dentistry.

Introduction

The teaching of surgical skills, which has traditionally followed an apprentice style approach, is now facing a number of challenges that are driving medical schools to seek alternatives. One challenge is that increasing enrollment combined with time constraints on the time of expert surgeons means that students typically do not receive as much supervised training as would be desirable. Rather, students end up spending a significant portion of their training time carrying out unsupervised practice. Furthermore, medical schools have little choice but to set requirements for surgical curricula in terms of amount of training time spent rather than in terms of level of proficiency achieved [1]. Even when assessment is carried out, it is by nature subjective, lacking sufficient standardization.

In response to these challenges, researchers have been developing new types of simulators and medical schools have been exploring the use of simulation in surgical training curricula. These efforts have particularly benefited from advances in virtual reality (VR) technology. VR simulators now exist for training in a variety of surgical domains, [2–6] and VR simulators have been introduced into dental curricula as training devices for clinical skill acquisition in several tasks [7, 8]. VR simulators enable collecting detailed data on relevant metrics throughout a procedure and thus provide a basis for detailed and objective procedure assessment. Indeed, a great volume of recent research has focused on developing metrics and techniques for objective assessment of surgical skill level [9–12]. Such analyses can be used for summative assessment and more excitingly for formative assessment by incorporating mechanisms for tutorial feedback generation into the simulators. But as research has progressed in this direction, researchers have come up against the complicating factor of the great variability with which any particular operation may be carried out [13, 14]. Such natural variability, not only in minute details of movement but also in style, poses a challenge for assessment. In domains where procedures may be carried out in multiple acceptable ways, an effective teacher must be able to recognize the style that a student is naturally using and provide corrective guidance relative to that style. This should also be the case for any simulator that generates tutorial feedback. To achieve this, the first challenge that must be solved is to recognize the style being used by a student even if it is being carried out incorrectly.

In this paper we present an approach to identifying the expert procedure from a set of stored procedures carried out in different styles that best match a student procedure. We make use of a VR dental simulator that we have developed for teaching dental procedures [6]. The system includes haptic feedback that can simulate tooth surface exploration and cutting for tooth preparation. It can automatically record performance and kinematic data on how experts and novices perform each step of a task, e.g., tool path, angulations and force used, which are not available in conventional skill training environments. For the present work we make use of only information about tool path and time.

Identifying stylistically similar procedures based metrics such as tool path and timing is challenging. Even if the expert and student are following the same basic path, the student movements are typically less smooth, resulting in differences in path location and path length. Velocity of movement of students is also typically slower than that of experts. Dynamic time warping (DTW) [15, 16] is a technique introduced for the analysis of handwriting that is designed to cope with some of these challenges. DTW determines the similarity of two trajectories of motion in cases where the trajectories may differ in terms of length and timing. In analysis of surgical procedures, DTW has been applied to the problem of spatio-temporal registration of trajectories for recognition of surgical gestures [17]. The present study aims to determine the potential of DTW in matching novices' tooth cutting sequences with those of experts for the task of performing access opening to the root canals.

Methods

Dental virtual reality simulator and on-line data collection

We developed VR simulator that operates on a standard PC with an Intel Core 2 Duo 2.8GHz CPU, 4 GB RAM, and an nVidia GeForce 9600GT video card with 512MB of RAM connected to a 15-inch monitor and two PHANToM Omni haptic devices in a dual configuration, representing a handpiece and a dental mouth mirror. (Figure 1). The PHANTOM Omni haptic devices (SensAble Inc., USA) allow six degrees of freedom positional sensing and generate three degrees of freedom force feedback with a maximum of 3.3 N. The simulation software was developed with C++, OpenGL, and OpenHaptics SDK (HDAPI). The tooth model was acquired using three-dimensional micro-CT (RmCT, Rigaku Co., Tokyo, Japan). Tomographic images were obtained using comprehensive dental imaging software (i-VIEW, Morita Co., Tokyo, Japan). Three-dimensional reconstruction was performed using 600 of these two-dimensional images processed by volume rendering. During simulation, a user could feel different force feedback when cutting through enamel, dentin, and pulp.

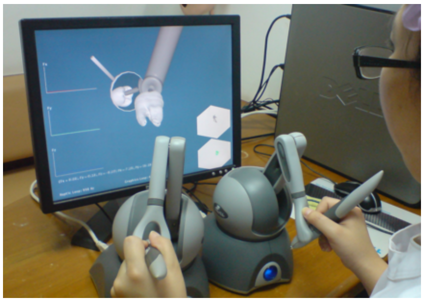

Figure 1 - A dentist performed access opening to the root canals with a haptic virtual reality simulator

Forty-four volunteers (40 fourth-year dental students (Novice), ages 20-23 years, and 4 dentists (Expert), ages 35-45 years) were enrolled in this study. All participants gave their written informed consent approved by the Institutional Ethical Review Board. Novices had experience using dental handpieces in cavity preparation from the operative preclinical course but no prior experience performing root canal treatment. Experts had professional training and experience in root canal treatment. All participants were right-handed. None of the participants had received any skill training using the haptic VR simulator.

All participants were briefly instructed on the use of the haptic VR simulator and the requirements of tooth preparation. The participants received a verbal explanation about the use of the system from the investigators and spent 15 minutes familiarizing themselves with the system interface, but not with the task. During this familiarization period, each participant was allowed to ask questions and receive further verbal explanation and suggestions from the investigators. After familiarization, the participants performed two trials of the task during which results were not recorded. The third trial was used for data collection. Participants were given the task of performing access opening to the root canals on the upper right first molar with the haptic VR simulator. The task was designed to mimic real access opening and to require hand-eye coordination for quality performance (Figure 1).

During data collection, data was gathered on elapsed time and kinematic variables with respect to the position of the handpiece in x, y and z direction, angulations of the handpiece with respect to x, y and z direction, transformation of the handpiece from the original position, drilling enabled/not enabled, position of the mirror in x, y and z direction, angulations of the mirror with respect to x, y and z direction, transformation of the mirror from the original position, and the force used in x, y and z direction.

Recognition of Clinical Process using DTW

Experts and novices performed operations on the dental simulator generating an output file which contained the kinematic attributes mentioned above in every millisecond. In this study, we selected the handpiece positions and movements as features for finding similarity between expert and novice and only the data when the user had enabled the drill for cutting was considered. Figure 2 shows the path of one expert and one novice in 3D space. Handpiece positions were normalized using $(X-\mu)/\sigma$, where X is the data sequence, μ is the mean and σ is standard deviation of those points.

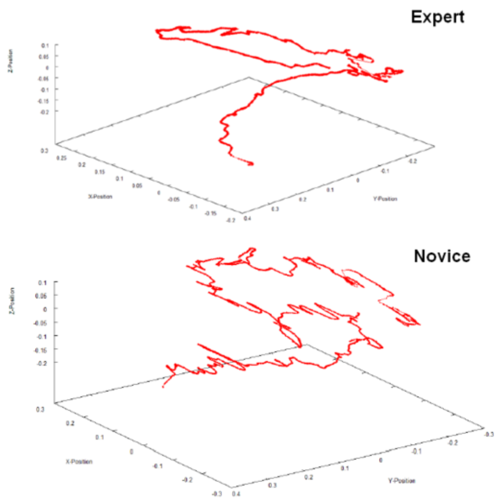

Figure 2 - Handpiece position in 3D generated from user's movement

Even when a novice is carrying out a procedure in the same basic way as an expert, the sequences of expert and novice movements will typically differ in length, positions, and speed. The expert's movements are usually more deliberate, economical and smooth throughout the operation. DTW is well suited to measuring similarity between sequences that may differ in speed and in which speed differences are not constant throughout the sequences. With DTW, the sequences are warped non-linearly in the time dimension to determine a measure of their similarity independent of non-linear variations in the time dimension but dependent on an application specific distance measure.

DTW [16] works as follows. Suppose we have two time series of length n and m respectively,

$$\text{Let } X = x_1, x_2, \ldots, x_n \text{ and } Y = y_1, y_2, \ldots, y_m$$

A matrix of size n by m is constructed such that the (i^{th},j^{th}) element of the matrix contains the distance $D(x_i,y_j)$ (in our case the Euclidean distance) between points i and j of the two series. After that, another matrix is constructed and the cost for each cell is determined using the condition:

- Initial Condition: $D(1,1) = 0$
- Recurrence: $D(i,j) = Dist(i,j) + min[D(i-1,j), D(i,j-1), D(i-1,j-1)]$

A warp path $W = w_1,w_2,...,w_k$ is constructed as the least cost path through the matrix from $(1,1)$ to (n,m) where k is the length of the warp path and the k^{th} element of the warp path is $w_k = (i,j)$. The warp path is typically subject to several constraints:

- Boundary conditions: The starting and ending points of the warp should be at two diagonally opposite ends of the matrix.
- Continuity: If $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a - a' < 1$ and $b - b' < 1$. This restricts the allowable steps in the warp path to be adjacent cells (including diagonally adjacent cells).
- Monotonicity: If $w_k = (a,b)$ then $w_{k-1} = (a',b')$ where $a - a' > 0$ and $b - b' > 0$. This forces the points in W to be monotonically spaced in time.

Finally, cost is calculated as:

$$Cost = \frac{\text{Total cost of warp path}}{k}$$

The length of the warp path (k) in the denominator is used because for different sequences warp paths may have different lengths.

Data Analysis

Four experts performed access opening to the root canals using different sequences of operations.

Expert1 cut into the palatal pulp horn followed by extending the opening laterally to the mesiobuccal canal orifice, then followed a clockwise path to the distobuccal canal orifice, and the palatal canal orifice.

Expert2 cut into the palatal pulp horn followed by extending the opening laterally to the distobuccal canal orifice, then followed a counter clockwise path to the mesiobuccal canal orifice, and the palatal canal orifice.

Expert3 performed an initial cavity half way to the pulp chamber using a clockwise path then cut into the palatal pulp horn followed by extending the opening laterally to the mesiobuccal canal orifice, then followed a clockwise path to the distobuccal canal orifice, and the palatal canal orifice.

Expert4 performed an initial cavity half way to the pulp chamber using a counter clockwise path then cut into the palatal pulp horn followed by extending the opening laterally to the distobuccal canal orifice, then followed a counter clockwise path to the mesiobuccal canal orifice, and the palatal canal orifice.

Forty students were randomly divided into 4 groups of 10 students each. Students in groups 1, 2, 3 and 4 were trained to perform access opening to the root canals following experts 1, 2, 3, and 4 respectively.

Data from novices and experts was gathered as previously described and DTW was applied to determine whether each novice could be matched to the expert who had trained him based on the movement patterns, thus recognizing the approach to the procedure being attempted by the novice. For each novice procedure, DTW was applied to calculate the similarity between that novice and each of the four expert procedures. The lowest cost was taken as the best match. Figure 3 shows the warp between one expert and one novice sequence. Notice that these two sequences were warped from the beginning to the end.

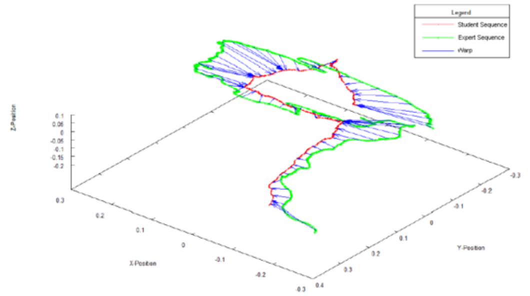

Figure 3 - Dynamic Time Warping between an expert and a novice sequence

The accuracy of the approach was computed as:

$$Accuracy = \frac{\text{Total number of correct matches}}{\text{Total number of students}} \times 100$$

Results

The data collection yielded 4 groups that differed widely for the tooth preparation sequence. Overall, the accuracy of the matching between novices and experts was very high (95%) compared to the probability of matching the sequences correctly by chance (25% in this four class problem). DTW correctly matched students in each group with the expert who trained them except for two cases. Case 1 was *Student8* (in group 1) who matched with *Expert2*, and case 2 was *Student24* (in group 3) who matched with *Expert1*.

In case 1, *Student8* should have matched *Expert1* but the lowest cost match was against *Expert2* at 170.45, with the match against *Expert1* being the next lowest at 339.54. The reason for this error can be seen from Figure 4. Figure 4(a) shows the sequences for *Student8* and *Expert1* and 4(b) shows the sequences for *Student8* and *Expert2*. The sequences in Figure 4(b) have initial segments that match closely, so DTW resulted in very low cost for the initial portion as compared to the sequences in Figure 4(a). Even though the cost was high for the later segment, the overall cost of the match between the sequences in 4(b) was lower than that in 4(a).

In case 2, *Student24* should have matched *Expert3* but the cost of the match against *Expert1* was lowest at 187.34 while the cost of the match against *Expert3* was only second lowest at 264.30. The reason for this mismatch can be seen from Figure 5. Figure 5(a) shows the sequences for *Student24* and *Expert3* while Figure 5(b) shows the sequences for *Student24* and *Expert1*. From Figures 5(a) and 5(b) it can be seen that the expert sequences were somewhat similar. The two expert sequences differ somewhat at the start but are similar at the

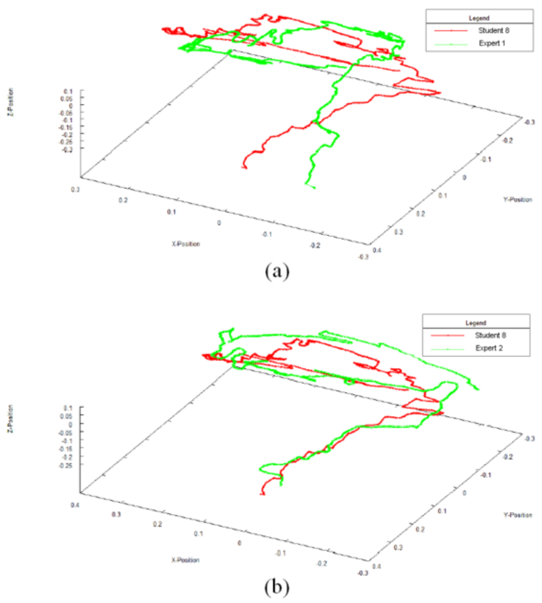

Figure 4 - Sequences of Student8 and Expert1 that should match (a) and sequences of Student8 and Expert2 that should not match but with lowest cost (b)

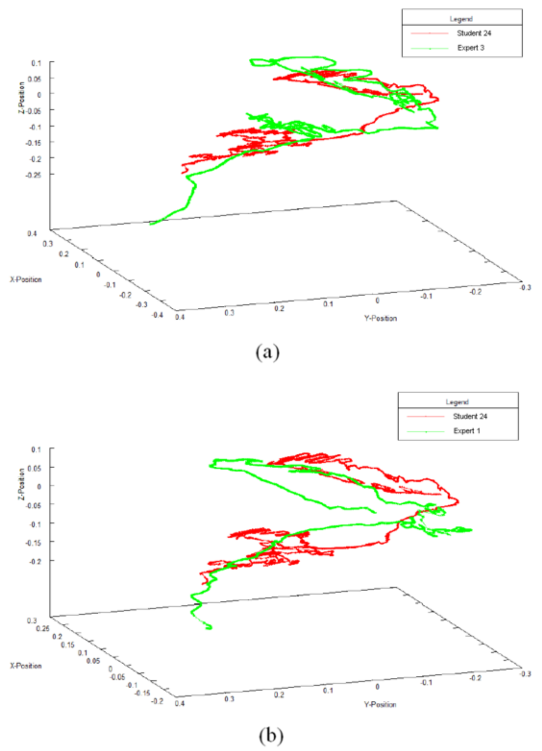

Figure 5 - Sequences of Student24 and Expert3 that should match (a) and sequences of Student24 and Expert1 that should not match but with lower cost (b)

later portions. Because of this, the costs of matching *Student24* with *Expert3* or *Expert* 1 were similar.

Discussion

Generally, knowledge of results (e.g., the pulpal depth was 1mm too deep) and knowledge of performance (e.g., was the handpiece held perpendicular to the long axis of the tooth when it should not have been) facilitate learning because they enable the performer to make appropriate adjustments to the movement on the next trial and increase the likelihood of the desired outcome will be achieved. In cases where procedures can be carried out using various alternative sequences, it is important to be able to recognize the correct sequence that a student is attempting in order to be able to provide effective corrective feedback. In this paper we have shown that metrics can be gathered from a virtual reality simulator that combined with dynamic time warping enable a student to be matched to the style of the expert who tutored him with a high degree of accuracy.

DTW seems to be a promising tool in the recognition of clinical performance in that it provides for objective evaluation of the trajectory of the instrument used to perform a dental procedure and is robust to differences in tool path length and velocity which differ greatly between novices and experts. The technique may enhance our understanding of the processes involved in clinical performance based on an unbiased assessment. Of course, the DTW technique alone cannot answer the question of how well a novice performs a task. Outcome measures need to be combined for comparison of outcomes under conditions where the movement trajectories are taxed, thus enabling analysis of their separate contributions to the outcome distortions in poor performance.

Conclusion

The current results suggest that DTW is useful technique to find the best matching expert for a student so that feedback based on that expert's performance can be given to the novice in clinical skill training. Several directions remain open for further work. First is the issue of improving the performance of the matching algorithm. In this paper we used only data of the tool location at each point in time. Performance could likely be improved by using information about trajectory of motion as well as information about other metrics such as force and angulation. The next step is to analyze the differences between the expert and novice procedures and identify those differences most relevant to quality of outcome for use in formative assessment. The final issue concerns how best to present this assessment information to the student to improve performance.

References

[1] Gallagher AG, Ritter EM, Champion H, Higgins G, Fried MP, Moses G, Smith CD, and Satava RM. Virtual reality simulation for the operating room: proficiency-based training as a paradigm shift in surgical skills training. Ann. Surgery 2005: 241: 346-72.

[2] Riva G. Applications of Virtual Environments in Medicine. Methods Inf Med 2003: 42 (5): 524-34.

[3] Färber M, Hummel F, Gerloff C, and Handels H. Virtual reality simulator for the training of lumbar punctures. Methods Inf Med 2009: 48: 493-501.

[4] dV-Trainer, www.mimicsimulation.com/products/dv-trainer/, 2014.

[5] Delorme S, Laroche D, DiRaddo R, and Del Maestro RF. NeuroTouch: a physics-based virtual simulator for cranial microneurosurgery training, Neurosurgery 2011: 71(1): 32-42.

[6] Rhienmora P, Haddawy P, Khanal P, Suebnukarn S, and Dailey MN. A Virtual Reality Simulator for Teaching and Evaluating Dental Procedures. Methods Inf Med 2010: 49(4): 396-405.

[7] Sohmura TH, Hojo H, Nakajima M, Wakabayashi K, Nagao M, Iida S, Kitagawa T, Kogo M, Kojima T, Matsumura K, Nakamura T, and Takahashi J. Prototype of simulation of orthognathic surgery using a virtual reality haptic device. Int J Oral Maxillofac Surg 2004: 33(8): 740-50.

[8] Steinberg AD, Bashook PG, Drummond J, Ashrafi S, and Zefran M. Assessment of faculty perception of content validity of PerioSim, a haptic-3D virtual reality dental training simulator. J Dent Educ 2007: 71(12): 1574-82.

[9] Megali G, Sinigaglia S, Tonet O, and Dario P. Modelling and evaluation of surgical performance using hidden Markov models. IEEE Trans Biomed Eng 2006: 53(10): 1911-9.

[10]Oropesa I, Sánchez-González P, Lamata P, Chmarra MK, Pagador JB, Sánchez-Margallo J, Sánchez-Margallo FM, and Gómez J. Methods and tools for objective assessment of psychomotor skills in laparoscopic surgery. J Surg Res 2011: 171(1): 81-95.

[11]Suebnukarn S, Phatthanasathiankul N, Sombatweroje S, Rhienmora P, and Haddawy P. Process and Outcome Measures of Expert/Novice Performance on a Haptic Virtual Reality System. J Dent 2009: 37(9): 658-65.

[12]Overby DW and Watson RA. Hand motion patterns of Fundamental of Laparoscopic Surgery certified and noncertified surgeons. Am J Surg 2014: 207: 226-30.

[13]Reiley CE, Lin HC, Varadarajan B, Vagvolgyi B, Khudanpur S, Yuh DD, and Hager GD. Automatic recognition of surgical motions using statistical modeling for capturing variability, Studies in Health Technology and Informatics 2008: 132: 396-401.

[14]Anderson DK. How can educators use simulation applications to teach and assess surgical judgement? Academic Medicine 2012: 87: 934-41.

[15]Brina CD, Niels R, Overvelde A, Levi G, and Hulstijn W. Dynamic time warping: A new method in the study of poor handwriting. Hum Move Sci 2008: 27(2): 242-55.

[16]Kruskal J and Liberman M. The symmetric time-warping problem: From continuous to discrete. In: Sankoff D and Kruskal J, eds. Time warps, string edits, and macromolecules: The theory and practice of sequence comparisons. Massachusetts (USA): Addison-Wesley, 1983.

[17]Padoy N and Hager DG. Spatio-Temporal registration of multiple trajectories. In: Fichtinger G, Martel A, and Peters T, eds. Medical Image Computing and Computer-Assisted Intervention – MICCAI 2011, Lecture Notes in Computer Science 2011: 6891: 145-52.

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