Proc. of the 9th Intl. Conf. of Asian Society for Precision Engg. and Nanotechnology (ASPEN 2022)
15–18 November 2022, Singapore. Edited by Nai Mui Ling Sharon and A. Senthil Kumar
doi://10.3850/978-981-18-6021-8_OR-08-0183

Extended Abstract for ASPEN2022(2~4pages)

Big Data and Artificial Intelligence (AI) Driven Dental Prostheses Design

Hao Ding[1], Zhiming Cui[2], Ebrahim Maghami[3], Yanning Chen[1], Jukka Matinlinna[1], Edmond Pow[4], Alex Fok[5], Michael Burrow[4], Wenping Wang[2,6] and James Tsoi[1,#]

1 Division of Applied Oral Sciences & Community Dental Care, Faculty of Dentistry, The University of Hong Kong, 34 Hospital Road, Sai Ying Pun, Hong Kong
2 Department of Computer Science, Faculty of Engineering, The University of Hong Kong, Pok Fu Lam, Hong Kong
3 Department of Mechanical Engineering and Mechanics, Drexel University, 3141 Chestnut Street, Philadelphia, PA 19104, USA
4 Restorative Dental Sciences, Faculty of Dentistry, The University of Hong Kong, 34 Hospital Road, Sai Ying Pun, Hong Kong
5 Minnesota Dental Research Center for Biomaterials and Biomechanics, School of Dentistry, University of Minnesota, 515 Delaware St. SE, Minneapolis, MN 55455, USA
6 Department of Visualization, College of Architecture, Texas A&M University, 789 Ross Street, 3137 TAMU College Station, TX 77843-3137, USA
Corresponding Author / Email: jkhtsoi@hku.hk, TEL: +852-2859-0515, FAX: +852-2548-9464

KEYWORDS: 3D-GAN, Artificial Intelligence, Dental crown design, CAD/CAM

OBJECTIVES: In prosthetic dentistry, Computer-Aided Design and Computer-Aided Manufacturing (CAD/CAM) has been widely used in the design and manufacturing process of dental crowns with high accuracy and efficiency compared with traditional way. Large amount of digitalised dental crown models have been created with the help of CAD. However, the digitalised prosthetic data is only used to assist CAM process. With the development of AI, big data and digital technologies, these data can be anticipated to guide the dental crown design process, thus achieving the transformation from knowledge-based design to big data driven design. In this work, a fully automatic dental crown design method by utilising AI and big data is presented with the potential of improving current partially digitalised dental crown design workflow.

METHODS: 500 sets of mandibular second premolars, their adjacent and antagonist teeth from healthy and young adults (19-22y.o.) were collected digitally, and machine learned with 3D-Deep Convolution Generative Adversarial Network (3D-DCGAN) approach. 12 sets of data were randomly selected as test dataset. The 12 natural teeth in the test dataset were compared with (1) our 3D-DCGAN design, (2) knowledge-based design (commercially available as CEREC), and (3) technician's design individually in parameters of 3D similarity, cusp angle, occlusal contact point number and area, and Finite Element (FE) static and fatigue simulation using Lithium disilicate ceramic as crown materials. The data were statistically analysed by SPSS 22.0 (IBM) at α=0.05.

RESULTS: 3D-DCGAN design and natural tooth had lowest discrepancy in morphology compared with other groups. Knowledge-based design showed a statistically significant ($p<0.05$) higher cusp angle compared with our 3D-DCGAN design and natural tooth. No significant difference was observed regarding the occlusal contact point number and area among all four groups. FE analysis results showed 3D-DCGAN design had a comparable performance with natural teeth regarding the stress distribution in crown, adhesive layer and dentine; the two groups also showed similar fatigue lifetimes under simulated cyclic loadings of 100-400 N.

CONCLUSION: Dental crowns designed by the big-data 3D-DCGAN method in this study showed no statistical differences among morphological, occlusal and mechanical parameters compared with natural teeth. This study demonstrated suitable AI can be utilised to design personalised dental crowns with high accuracy.

1. Introduction (Times New Roman 10pt)

In prosthetic dentistry, single crowns restoration is the most common procedure in the US [1], the global market of dental crowns and bridges will further increase at a compound annual growth rate (CAGR) of 7.78% to USD 3.8 billion in 2026 [2]. Traditionally, this process is completed by impression taking, gypsum mould and metal casting, ceramic firing and plastic PMMA flasking. All these are labour-intensive and time-consuming, in addition, the dusts generated in the process could generate health and environmental hazards.

Proc. of the 9th Intl. Conf. of Asian Society for Precision Engg. and Nanotechnology (ASPEN 2022)
15–18 November 2022, Singapore. Edited by Nai Mui Ling Sharon and A. Senthil Kumar

Computer-Aided Design and Computer-Aided Manufacturing (CAD/CAM) has been widely used in dentistry for over 3 decades, which enables fast and accurate design and manufacturing of the dental prostheses. However, it still encounters problems such as lack of accuracy, expensive and still needing human to operate.

Current dental prostheses CAD software mainly utilises library approach, which includes hundreds of standard crowns, further adjustments are still needed by the operator to meet patients' individual conditions. The adjustments are mainly based on factors such as distance between crown and adjacent teeth as well as the opposite dentition. Large amount of digitilised crown designs are generated every year, but those data can be only used to assist CAM process according to current workflow. With the development of AI, big data and digital technologies, more and more applications can be finished automatically by machine itself. In restorative dentistry, these crown data can be anticipated to guide the dental crown design process, thus achieving the transformation from knowledge-based design to big data driven design. In this work, a fully automatic dental crown design method by utilising AI and big data is presented with the potential of improving current partially digitalised dental crown design workflow.

2. Materials and Methods

2.1 Dataset

In the study, 3D digital dental prostheses dataset including 600 healthy dental stone models with full arches of both upper, lower jaws and occlusal relationship was obtained with informed consent (IRB Reference Number: UW 21-571). The impression and casts were prepared and scanned by Cerec Omnicam (Sirona Dental Systems, Bensheim, Germany). STL files of the cast models were exported from the CEREC Software 4.6 (Sirona Dental Systems, Bensheim, Germany). In this study, tooth Number 44, 45, 46 and 47 (Figure 1) in the ISO 3950 notation system are segmented manually in the software Meshlab [3] and reserved for GAN model training.

As shown in Fig. 1, tooth No. 45 is the target teeth for crown generation. Each set of the training data includes three teeth including Nos. 44, 45 and 46 teeth (Fig. 1A). A masked No. 45 tooth is prepared (Fig. 1B), representing the missing tooth which the crown needs to be designed. Its adjacent teeth (Nos. 44 and 46) are used as a reference for ML training, i.e. the ML algorithm generates the No.45 crown based on the information of Nos. 44 and 46.

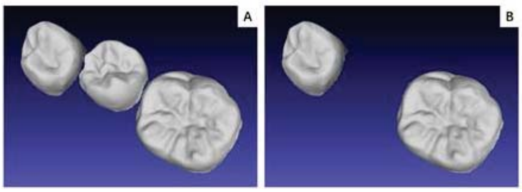

Fig. 1 Training dataset A) No. 44, 45, 46 tooth; B) No. 44, 46 tooth.

2.2 GAN Training

3D-DCGAN was adopted to train the ML model. The network was built on PyTorch platform. The generator model consisted of four deconvolution layers with the number of filters as 128-64-32-1. Kernel size, stride and padding size were set as 3*3*3, 1, 1, respectively. A Tanh function was used at the last layer of the generator. The discriminator model consisted of four convolution layers, reflecting the same structure of the generator, except for the stride was set as 2 and a Sigmoid function was applied at the last layer of the discriminator. Batch normalization was applied after every convolutional layer. LeakyReLUs were used in both generator and discriminator models with a slope of 0.2.

The training was performed on a desktop computer with configurations of Intel(R) Xeon (R) W-2123 3.6 GHz CPU, an Nvidia GeForce RTX 2080 Ti GPU and 16GB RAM. Different parameters such as learning rate, batch size, number of epochs and training data were investigated to find the optimal parameters. To monitor the quality of the generated tooth morphology with the epochs increases, the interval between image sampling was set as 400, *i.e.* the training results were exported and saved every 400 epochs.

2.3 Quality Evaluation

Twelve additional cases were randomly selected as the testing dataset, and twelve crowns were generated with the trained 3D-DCGAN. These AI crowns were compared with the original natural tooth (NT), CEREC biogeneric individual design (BI), and technician CAD (Zfx Manager 2.0) design (TD) operated by one experienced dental technician in the parameters of cusp angle, 3D similarity, occlusal contact, static and dynamic Finite Element (FE) analysis.

3. Results

3.1 Cusp Angle

The mean cusp angles of NT, AI, BI and TD groups were respectively 54.05°, 49.43°, 67.11° and 63.34°. NT group had a significantly lower mean cusp angle compared with BI group; while BI and TD group had significant higher mean cusp angles than AI group. No significant differences were found between NT and AI, and NT and TD groups, respectively.

3.2 3D Morphology Comparison

Discrepancies of crown designs in AI, BI and TD groups were compared pairwise with NT group. The numerical comparison results are listed in Table 1.

Table 1 Comparison of the mean discrepancies of premolar crowns designed by AI, BI and TD groups with NT group.

Groups	Mean Positive Deviation (SD)	Mean Negative Deviation (SD)	Root Mean Square (SD)
NT *vs.* AI	0.2502 (0.0494)^{a}	-0.3106 (0.1215)^{d}	0.3611 (0.1160)^{f}
NT *vs.* BI	0.3480 (0.0576)^{b}	-0.4379 (00883)^{e}	0.5065 (0.0700)^{g}
NT *vs.* TD	0.2919 (0.0455)^{c}	-0.3894 (0.1183)^{e}	0.4550 (0.1019)^{g}

*Different superscript letters indicate significant differences ($p<0.05$)

As indicated in Table 1, NT vs. AI group exhibited statistically significant lowest discrepancies by means of Mean Positive Deviation (MPD), Mean Negative Deviation (MND) and Root Mean Square (RMS). The discrepancies between NT vs. BI group and NT vs. TD group were not statistically significant in the latter two measured items

(MND and RMS). Besides, NT vs. BI group exhibited a significantly lower MPD value compared with TD vs. NT group.

3.3 Occlusal Contact

Two types of virtual articulating paper with the thicknesses of 100 µm and 200 µm were used. Occlusal contact point number and area were measured for all groups. Fig. 2 revealed the mean contact point number and area for groups NT, AI, BI and TD. No significant difference was found in contact point numbers and areas for 100 and 200 µm articulating papers among the four groups.

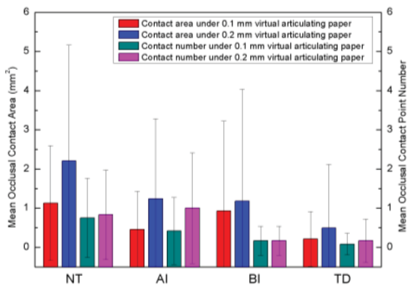

Fig. 2 Mean occlusal contact point number and area of crowns within different groups.

3.4 Finite Element Analysis

The stress distributions of adhesive resin cement layer and abutment under physiological occlusal forces (300 N) for AI group are shown in Fig. 3. The corresponding numerical value of stresses for all four groups are illustrated in Table 2, the areas around the central fossa and contact point were selected for each sample for measurement.

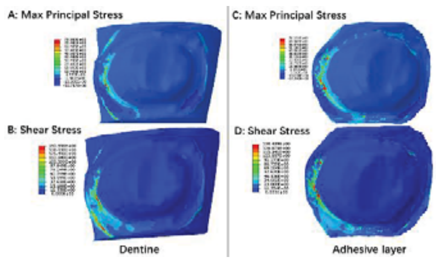

Fig. 3 Max principal stress (A,C) and Tresca (Shear) stress (B,D) of tooth preparation (A,B) and adhesive cement layer (C,D) for AI group.

Table 2 Stress distribution of crowns, maximum principal and shear stress in adhesive layer and dentine area with different designs subjected to physiological occlusal forces.

Groups	Stress Distribution on Crown		Max Stresses on Dentine		Max Stresses on Adhesive Layer	
	Central Fossa Area (MPa)	Around Contact Area (MPa)	Max. Principal Stress (MPa)	Max. Shear Stress (MPa)	Max. Principal Stress (MPa)	Max. Shear Stress (MPa)
NT	23.97	24.13	74.79	147.16	67.22	41.00
AI	26.73	28.48	79.98	150.60	70.25	138.41
BI	20.04	18.90	60.79	125.30	63.18	110.05
TD	40.72	54.18	72.22	155.66	74.71	160.43

In general, as Table 2 shows, the stresses at the central fossa area were lower than those at the contact point area, except for BI group. TD had the highest values of stresses in both measured areas. In the inner layers of the crown (adhesive layer and dentine), the maximum principal stresses and shear stresses varied. AI group had the highest maximum principal stress followed by NT, TD and BI in dentine; while in the adhesive layer, TD had the highest maximum principal stress followed by AI, NT and BI. An obvious distinction was found in the maximum shear stress for TD group, in which the number was 2.5-4 times lower than the other groups.

As shown in Fig. 3, the maximum principal stress and maximum Tresca (shear) stress of the adhesive layer and dentine were found in the shoulder area, while no stress concentrations were found on the occlusal directions in the adhesive layer and dentine as expected, as the shoulder area should be the main load bearing structure.

Estimation of fatigue life circles was calculated. As illustrated in Fig. 4, AI had the closest estimated fatigue lifetime compared with NT. AI could achieve *ca.* 10e32 (10^{32}) cycles lifetime at the area near the contact area and *ca.* 10e35 (10^{35}) cycles at the central fossa area under 400N loading, while the numbers in NT group were determined as *ca.* 10e38 (10^{38}) for both areas.

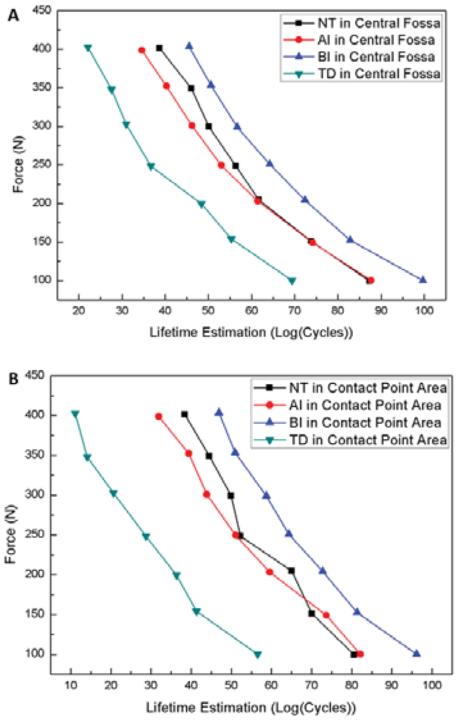

Fig. 4 Force *vs.* lifetime estimation (in log scale) for crowns in (A) central fossa area and (B) contact point area.

4. Discussion

AI-generated crowns by 3D-DCGAN revealed a higher degree of similarity compared with natural teeth (NT) morphology regarding cusp angle, MPD, MND and RMS, and fatigue biomechanics than BI and TD groups. The proposed 3D-DCGAN learned from natural teeth, while BI and TD have different mechanisms. BI utilised a tooth library and adjustments were needed by a technician. With regards to TD, as there were no regulated standards for the design of occlusal surfaces, the position and dimension of the design such as groves and cusps varied. Different technicians might have their preferences and ideas. Current designs mainly rely on an intra-oral 'try-in' of a crown to evaluate its quality, if patients found no discomfort or a 'high' bite, then this design is regarded as acceptable. These design aspects, however, are shown in this study that can affect the biomechanical performance and thus showing different fatigue life-times (Fig. 4). The tiny difference in the design played an essential role regarding the long-term success rate.

This study has seminally evaluated the biomechanical performance of an AI-generated 3D dental subject using an *in silico* fatigue developed by Homaei *et al.* [4], that is a dynamic non-linear FE model encompassed of multi-layered teeth, materials (crown and resin cement) and design. This model has shown a close match about the simulated fatigue lifetimes and experiment results for premolar crowns with different materials. Ideally, the FE analysis estimates the fatigue properties based on material type, stress distribution, Young's modulus and Poisson's ratio, *etc*. Although the simulated fatigue lifetimes are representing the ideal condition that might have certain deviations compared with experiment results, the numbers still have good correlations at least in terms of consistency. As such, higher fatigue lifetimes in numerical simulation may be incurred due to the material used in the experimental setup might have some nonhomogeneity structures or the interfaces between ceramic, adhesive layer and dentine may not have constant elastic moduli or strength.

In FE analysis, the amount of loading applied on the indenter was determined based on the average fatigue failure loads in an experimental study [5]. In the previous study [6], S–N fatigue curve for LD dental ceramic was formulated. Using the fatigue properties of LD material from the reported S-N curve and finding the stress value in the presented ceramic crowns, the number of cycles under loading can be calculated by the nonlinear Basquin formula [7, 8]. The present study has considered different occlusal forces (from 100 to 400 N). For each load, the stress values were computed. To compare the lifetime of each crown design in informative approach for the readers, the Force vs. Lifetime curve (F-N curve) was demonstrated. This representation provides valuable information on the lifetime of different crown designs and their relationships with exceeding loadings. However, it should be noted that the estimated lifetime based on the FE analysis have some limitations. Due to the complex geometry of dental crowns, various parameters such as the degree of polished surface and possible existence of microcracks might affect the failure phenomena. For instance, monitoring the initiation of a microcrack can provide more insightful data on lifetime of a ceramic crown rather than recording maximum stress, Thus, the FE models in the presented study can be improved with various advanced computational methods to estimate lifetime [9-11].

5. Conclusions

We proposed a new approach to design dental crowns based on an AI algorithm (3D-DCGAN) that has shown the least discrepancy with natural teeth compared with BI and TD. In terms of occlusal contact point and area, 3D-DCGAN, BI and TD are comparable occlusal relationships matched better with natural teeth. Regarding the fatigue properties of lithium disilicate crown, dynamic FE analysis revealed that no stress concentration was found for 3D-DCCAN designed crowns and the estimated lifetime was best matched with natural teeth.

ACKNOWLEDGEMENT

This work is submitted in partial fulfilment of the requirements of the degree of PhD for the first author at the Faculty of Dentistry, The University of Hong Kong. This research study is supported by a grant from the Research Grants Council, Hong Kong (17120220).

REFERENCES

1. The American College of Prosthodontists. *Facts & Figures*. 2021 [cited 2022 July 21]; Available from: https://www.gotoapro.org/facts-figures/.
2. Grand View Research Inc., *Dental Crowns And Bridges Market Size, Share & Trends Report Dental Crowns And Bridges Market Size, Share & Trends Analysis Report By Material (Titanium, Zirconium), By Price (Premium, Value, Discounted), By Region, And Segment Forecasts, 2019 - 2026*. 2018.
3. Cignoni, P., et al., *Meshlab: an open-source mesh processing tool*, in *Eurographics Italian Chapter Conference*. 2008, Salerno, Italy. p. 129-136.
4. Homaei, E., et al., *Numerical fatigue analysis of premolars restored by CAD/CAM ceramic crowns.* Dental Materials, 2018. **34**(7): p. e149-e157.
5. Homaei, E., et al., *Fatigue resistance of monolithic CAD/CAM ceramic crowns on human premolars.* Ceramics International, 2016. **42**(14): p. 15709-15717.
6. Homaei, E., et al., *Static and fatigue mechanical behavior of three dental CAD/CAM ceramics.* Journal of the Mechanical Behavior of Biomedical Materials, 2016. **59**: p. 304-313.
7. Yahyazadehfar, M., et al., *Fatigue of the resin–enamel bonded interface and the mechanisms of failure.* Journal of the Mechanical Behavior of Biomedical Materials, 2013. **21**: p. 121-132.
8. Mutluay, M.M., et al., *Fatigue of the resin–dentin interface: A new approach for evaluating the durability of dentin bonds.* Dental Materials, 2013. **29**(4): p. 437-449.
9. Carrara, P., et al., *A framework to model the fatigue behavior of brittle materials based on a variational phase-field approach.* Computer Methods in Applied Mechanics and Engineering, 2020. **361**: p. 112731.
10. Maghami, E., R. Pejman, and A.R. Najafi, *Fracture micromechanics of human dentin: A microscale numerical model.* Journal of the Mechanical Behavior of Biomedical Materials, 2021. **114**: p. 104171.
11. Desmorat, R., F. Ragueneau, and H. Pham, *Continuum damage mechanics for hysteresis and fatigue of quasi-brittle materials and structures.* International journal for numerical and analytical methods in geomechanics, 2007. **31**(2): p. 307-329.