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Accurate estimation of 6-DoF tooth pose in 3D intraoral scans for dental applications using deep learning

Key words: Artificial intelligence; Digital dentistry; Deep learning; Orthodontics; Tooth pose; Neural network

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Motivation

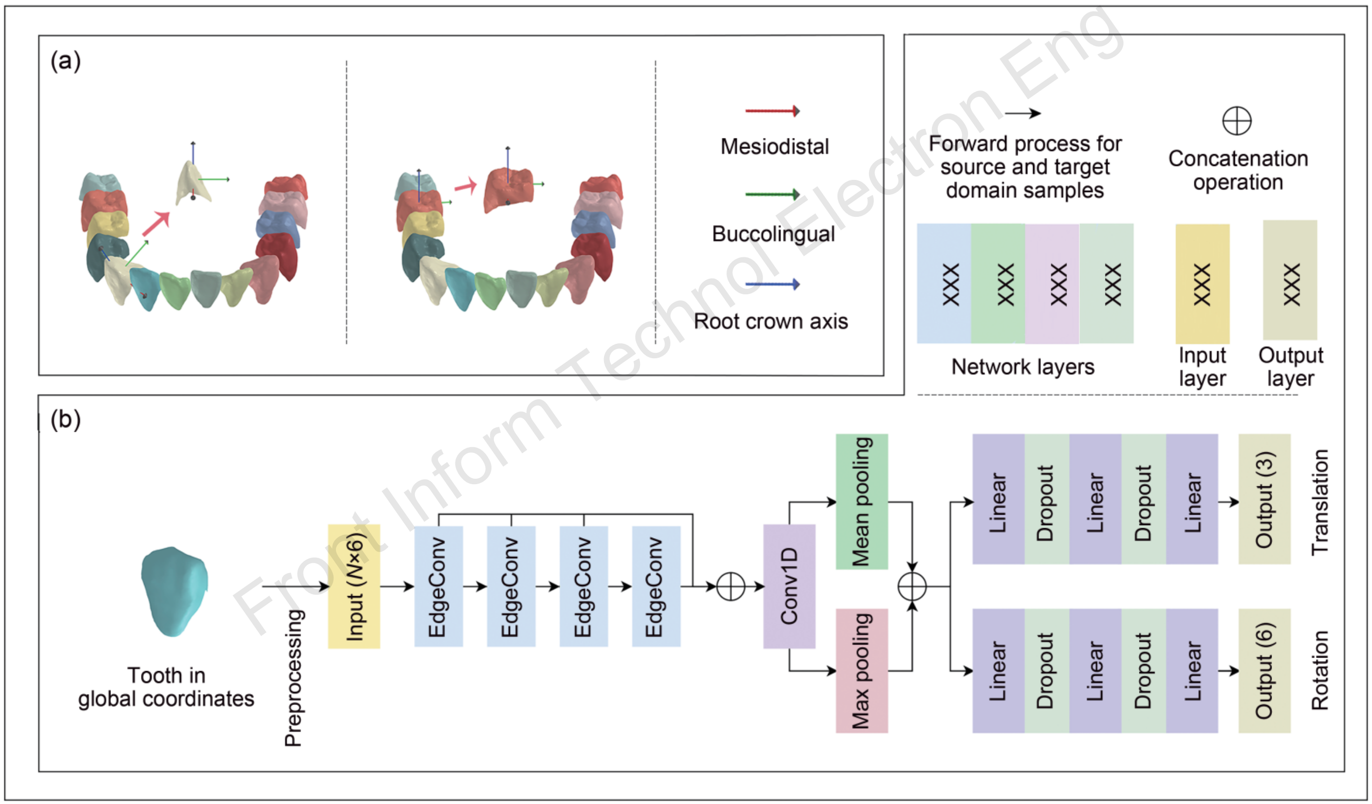
- Highly efficient and accurate treatment planning is of intense research interest to the field of digital dentistry, and many efforts are being made to achieve these goals, such as those devoted to model preparation, tooth segmentation, and tooth alignment. However, it is still challenging to precisely model the coordinates or pose of individual teeth in digital models, especially with high degrees of freedom.
- Accurate tooth pose enables the precise simulation of three-dimensional (3D) tooth movement and can help elucidate the optimal force magnitudes and directions in orthodontics and implants. Current solutions used in clinical software require heavy manual work, which is time-consuming. An accurate and efficient system that can automatically characterize individual tooth pose in digital dental models is needed to fully automate the treatment planning process.

Main idea

- We propose a novel, automatic, and efficient model for accurate tooth pose estimation using deep learning to address this challenge.
- We have built a large dataset with 12 991 patients (358 481 tooth scans), and each tooth is associated with an annotated rigid transformation provided by human experts.
- We have designed a novel neural network based on Edge-Conv blocks and resolved the tooth pose estimation problem with two jointly optimized tasks by estimating the corresponding translation and rotation transformations.

Method

1. Data preprocessing and statistics and deep learning based tooth pose estimation



Problem formulation and overview of TP-Net: (a) visualization of tooth pose estimation by predicting its orientation and location; (b) detailed architecture design of TP-Net, which consists of a feature extractor backbone and a two-branch estimation head

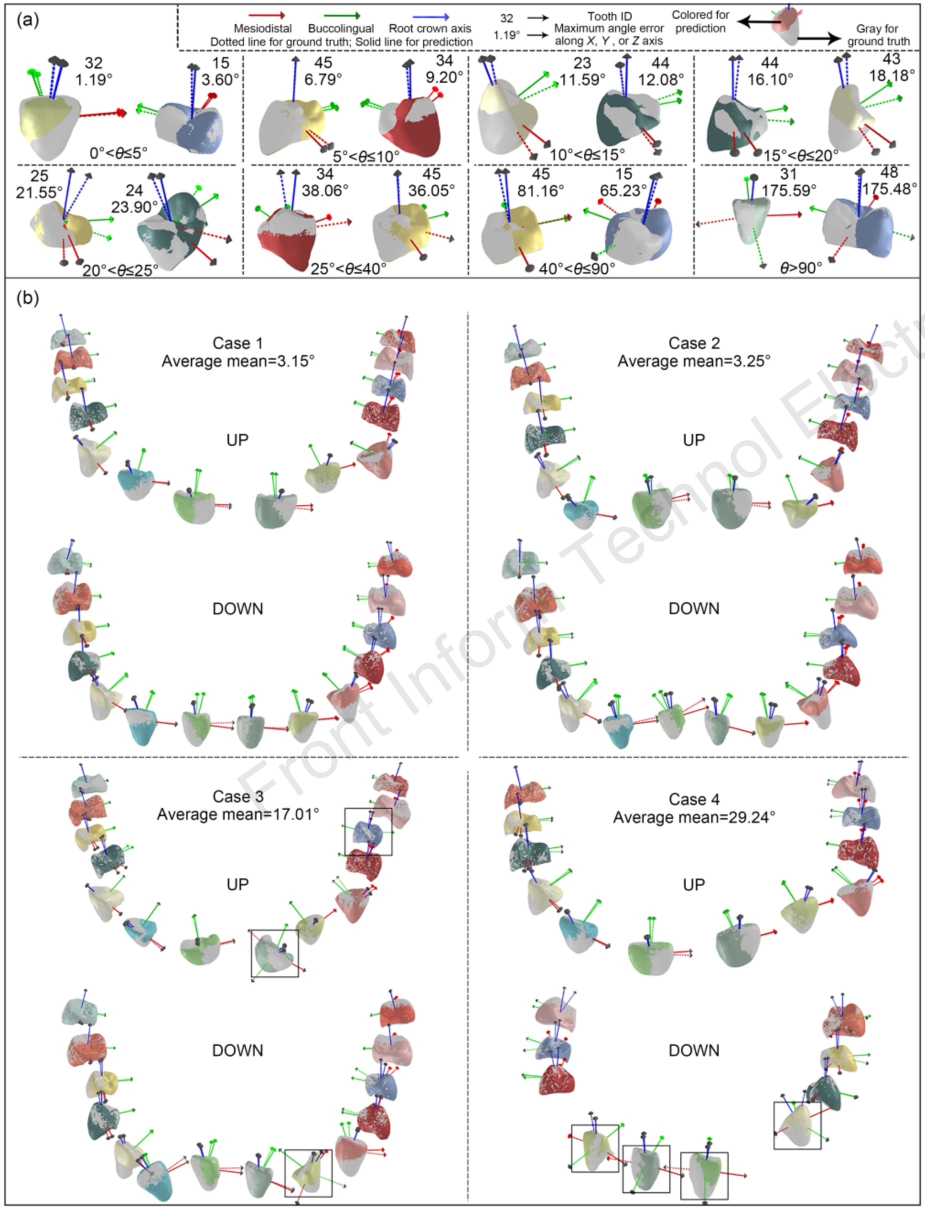
Method

2. Experimental setup and evaluation

We conducted a comprehensive ablation study on a small dataset, consisting of 1500 patients (80% for training and 20% for testing) randomly selected from the whole dataset, to evaluate the effectiveness of each loss function. We chose a popular deep learning method, PointNet, for point cloud processing, as our baseline. The overall performance was reported with the large dataset.

We evaluated the translation and rotation results for tooth pose estimation separately. The translation error was measured by the average L1 and L2 norms between the estimated and actual translation vectors. As for the rotation, we reported the average geodesic distance L_g, as well as the average Euler angle error along the Cartesian X-, Y-, and Z-axis, i.e., X_e, Y_e, and Z_e. We further demonstrated the clinical and industrial utility by comparing the inference time of our method with that of human experts. More statistical analyses and visualizations were also reported.

Major results



Visualizations of estimated orientation and ground truth: (a) visualization of multiple teeth with different scales of Euler angle errors; (b) visualization of four patients with small or large mean angle errors

Major results

Table 1 Pose estimation results for TP-Net*

Model	Loss	G_e	X_e (°)	Y_e (°)	Z_e (°)	L_1 (mm)	L_2 (mm)
PointNet	r+t+g	14.469	11.326	13.068	9.202	6.215	4.259
PointNet++	r+t+g	14.786	10.114	11.703	8.167	1.254	0.842
PointCNN	r+t+g	14.957	12.865	13.024	8.839	0.952	0.644
MinkCNN	r+t+g	12.368	10.631	11.524	8.271	1.017	0.718
M_s	r+t+g	11.607	9.628	10.061	7.355	1.313	0.884
M_s	r+t	13.229	10.721	11.807	8.184	0.963	0.650
M_s	g+t	13.236	10.722	11.812	8.182	1.060	0.715
M_l	r+t+g	6.863	5.265	5.979	4.780	0.633	0.446

* Tested on 300/2598 patients. r: rotation loss; t: translation loss; g: geodesic loss. s: small dataset with 1200 patients for training; l: large dataset with 10 393 patients for training. G_e: geodesic error; X_e, Y_e, Z_e: angle errors along the X, Y, and Z axes for rotation, respectively. L_1, L_2: L1 and L2 loss for translation, respectively

Major results

Table 2 Percentiles of the estimated angle errors from M_1^*

Angle error	p_{max}	p_{mean}	Angle error	$\dot{p}$
≤ 5°	41.56%	56.25%	≤ 4°	5.39%
≤10°	84.85%	92.47%	≤ 5°	42.19%
≤ 15°	95.95%	98.29%	≤ 6°	78.29%
≤ 20°	98.52%	99.32%	≤ 7°	93.03%
≤ 25°	99.22%	99.66%	≤ 8°	97.69%
≤ 40°	99.80%	99.90%	≤ 10°	99.54%
≤ 90°	99.94%	99.96%	≤ 13°	99.92%
> 90°	0.06%	0.04%	≤ 30°	100%

* Tested on 2598 patients/77 870 teeth. p_{max}, p_{mean}: percentiles of the maximum and mean angle errors θ_{max} and θ_{mean} for all teeth, respectively. $\dot{p}$: percentile of the mean angle error $\dot{\theta}$ for all patients. For each tooth, $\theta_{max}=\max(X_e, Y_e, Z_e)$, $\theta_{mean}=\frac{1}{3}(X_e + Y_e + Z_e)$. For each patient, $\widehat{\theta}=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{3}(X_e^i + Y_e^i + Z_e^i)$, where n is the number of teeth for the patient

Major results

Table 3 Mean and standard deviation of the predicted angle error from M_1^*

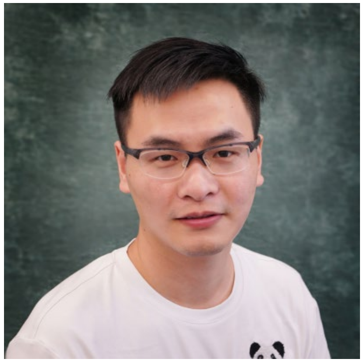
Tooth	X_e (°)	Y_e (°)	Z_e (°)	Tooth	X_e (°)	Y_e (°)	Z_e (°)
11	3.479 (4.242)	4.504 (4.655)	4.107 (2.723)	31	3.374 (5.540)	4.990 (5.641)	4.699 (2.488)
12	5.218 (3.958)	5.769 (4.077)	4.436 (2.667)	32	3.600 (5.381)	4.079 (5.547)	3.796 (2.448)
13	5.995 (4.994)	6.293 (5.017)	4.678 (2.861)	33	6.412 (4.849)	6.092 (4.666)	4.576 (3.027)
14	5.173 (5.391)	6.102 (5.667)	5.182 (2.902)	34	7.014 (5.711)	8.357(5.871)	6.287 (3.869)
15	5.778 (8.018)	6.445 (8.049)	4.782 (2.899)	35	8.213 (9.143)	**9.501 (9.241)**	6.569 (4.084)
16	3.751 (2.589)	4.096 (2.730)	3.375 (2.127)	36	4.576 (2.970)	5.955 (3.301)	4.537 (2.896)
17	5.738 (3.666)	5.425 (3.597)	5.069 (3.141)	37	5.831 (3.987)	6.679 (4.250)	5.543 (3.592)
18	8.993 (5.879)	8.497 (5.384)	7.389 (4.574)	38	**10.870 (8.715)**	**10.640 (7.608)**	**9.793 (7.251)**
21	3.249 (2.446)	4.323 (3.229)	4.249 (2.905)	41	3.632 (4.261)	4.239 (4.466)	3.558 (2.444)
22	4.667 (4.202)	5.319 (4.522)	4.322 (2.867)	42	3.609 (2.688)	4.848 (3.185)	4.418 (2.736)
23	6.093 (6.306)	6.473 (6.235)	5.180 (2.980)	43	5.720 (4.897)	5.644 (4.838)	4.277 (2.836)
24	5.252 (5.203)	5.739 (5.275)	4.546 (2.721)	44	6.537 (4.834)	7.649 (5.026)	5.682 (3.465)
25	6.619 (10.750)	6.822 (10.780)	4.596 (2.657)	45	7.567 (7.493)	**9.574 (7.468)**	6.532 (3.925)
26	4.102 (2.902)	4.298 (2.963)	3.215 (2.017)	46	4.173 (3.070)	5.153 (3.603)	4.165 (2.864)
27	5.916 (3.728)	5.875 (3.663)	5.177 (3.226)	47	5.264 (3.688)	6.433 (4.071)	5.744 (3.615)
28	**9.291 (5.347)**	**9.468 (5.334)**	7.877 (4.472)	48	**9.246 (8.158)**	**9.089 (6.812)**	8.179 (6.154)

* Trained with weighted sum loss and tested on 2598 patients, and the standard deviation is included in the brackets. X_e, Y_e, and Z_e denote angle errors along the X, Y, and Z axes, respectively. Bold numbers indicate the worst angle errors or errors larger than 9°

Conclusions

- We proposed an accurate and automatic 6-DoF tooth pose estimation system. The system showed good feasibility with a large dataset and has been integrated into a real-world clinical orthodontic system to assist dental diagnosis in orthodontics.
- Our work revealed that deep learning and artificial intelligence possess great potential for developing more intelligent and efficient digital dental solutions.

Wanghui DING, MD, chief physician, master's degree supervisor. He is with the Stomatology Hospital, School of Stomatology, Zhejiang University School of Medicine. He is a member of the Oral Health Big Data Specialist Alliance, a volunteer member of the Committee on Integrated Traditional Chinese and Western Medicine of the Chinese Volunteer Association, a youth member of the Sleep Medicine Professional Committee of the Chinese Medical Doctor Association, a committee member of the Orthodontics Special Committee of Zhejiang Province, and a committee member of the Sleep Medicine Professional Committee of the Zhejiang Medical Association. His research focuses mainly on digital diagnosis and precise aesthetic invisible orthodontics, multidisciplinary collaborative diagnosis and treatment of oral breathing in children, and new techniques in fixed orthodontics guided by dental biomechanics.



Zuozhu LIU, assistant professor, is with Zhejiang University–University of Illinois at Urbana-Champaign Institute (ZJUI). Prior to joining ZJUI, he was a research fellow from the Department of Statistics and Applied Probability in National University of Singapore (NUS). Prior to joining NUS, he obtained his PhD degree from Singapore University of Technology and Design in 2019 under the guidance of Prof. Tony Q.S. QUEK and Prof. Shaowei LIN, and his BE degree from Zhejiang University in 2015. During his PhD study, he visited the RIKEN AIP Japan, working with Dr. Emtiyaz KHAN on Bayesian deep learning, and was intern at Preferred Networks Inc. in Tokyo, working on deep reinforcement learning. His research focuses mainly on unsupervised machine learning and AI for healthcare, and he is also interested in various deep learning applications.