Model Adaptive Tooth Segmentation

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Abstract

Automatic **3D tooth segmentation** on intraoral scans (IOS) plays a pivotal role in computer-aided orthodontic treatments. In practice, deploying existing well-trained models to different medical centers suffers from two main problems: (1) the data distribution shifts between existing and new centers, (2) the data in the existing center is usually not allowed to share while annotating additional data in the new center is time-consuming and expensive. In this paper, we propose a **Model Adaptive Tooth Segmentation** (MATS) framework to alleviate these issues. Taking the trained model from a source center as input, MATS adapts it to different target centers without data transmission or additional annotations, as inspired by the source data-free domain adaptation (SFDA) paradigm. The model adaptation in MATS is realized by a tooth-level feature prototype learning module, a progressive pseudo-labeling module and a tooth-prior regularized information maximization loss. Experiments on a dataset with tooth abnormalities and a real-world cross-center dataset show that MATS can consistently surpass existing baselines. The effectiveness is further verified with extensive ablation studies and statistical analysis, demonstrating its applicability for privacy-preserving tooth segmentation in real-world digital dentistry.

The framework of our MATS.

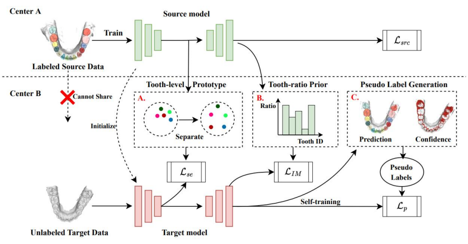
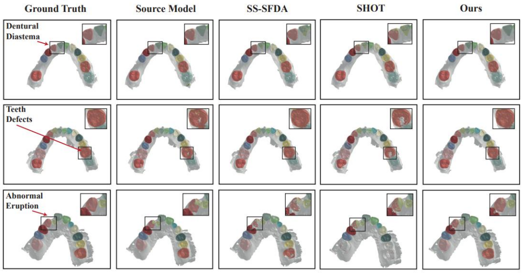


Figure 1: The framework of our MATS.

Visualization cases of segmentation.



Segmentation performance

Models	$\mathcal{D}_s$	DD			TD			ATE		
		mIoU	DSC	Acc	mIoU	DSC	Acc	mIoU	DSC	Acc
Source only	✓	83.76	88.00	94.04	80.38	86.02	91.62	83.60	88.32	93.58
DAN	✓	78.65	82.75	90.95	80.04	85.08	90.73	80.74	85.15	91.11
PointDAN	✓	84.05	87.79	94.11	85.02	90.17	93.57	82.25	86.46	92.07
MSL	✓	86.65	89.93	95.02	85.48	89.83	94.41	86.46	91.30	94.89
AdaptSegNet	✓	85.99	89.36	95.23	86.57	90.41	94.67	81.41	86.74	92.41
SHOT		83.66	87.63	93.60	85.55	89.48	94.00	87.30	91.02	94.98
AdaMI		84.31	87.92	94.63	83.52	88.42	93.20	87.00	90.86	94.83
SS-SFDA		86.36	89.82	95.01	86.11	90.38	94.04	85.38	89.67	94.06
Ours		**87.90**	**90.99**	**95.38**	**87.32**	**91.22**	**94.61**	**87.32**	**91.10**	**94.98**
Oracle		91.38	94.36	96.26	90.46	93.26	95.84	92.32	94.82	96.88

Ablation Study

f_s	$\mathcal{L}_{IM}$	$\mathcal{L}_{se}$	$\mathcal{L}_p$	mIoU (%)	DSC (%)	Acc (%)
✓				83.76	88.00	94.04
✓	✓			84.31	87.92	94.63
✓		✓		45.47	56.82	73.73
✓			✓	11.93	15.93	21.43
✓	✓	✓		87.53	90.67	95.39
✓	✓		✓	86.63	89.99	95.05
✓	✓	✓	*	86.14	90.30	94.03
✓	△	✓	✓	86.58	89.75	95.33
✓	✓	✓	✓	87.90	90.99	95.38

Figure 2: Ablation study of the losses. The "△" represents $\mathcal{L}_{IM}$ without tooth-ratio prior. The "*" represents unweighted $\mathcal{L}_p$.

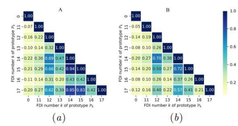


Figure 3: Cosine similarity between different prototypes (0, 11-17).

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