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REAL-TIME SURGICAL NAVIGATION IN ORAL MAXILLOFACIAL SURGERY USING AUGMENTED AI AND DEEP CNNS

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ABSTRACT

Real-time intraoperative navigation during Oral and maxillofacial surgery (OMS) is essential for achieving accuracy and for a safe operation. In this paper, we show a modified artificial intelligence (AI) framework based on deep CNNs that can automatically execute segmentation, registration, and visualization for intricate maxillofacial structures. The platform combines a deep learning model with an AR interface that displays key anatomy on the operative field as the procedure is being performed. Results shown that the proposed method can obtain high segment accuracy and robust tool tracking to enhance the intra-operative decision and improve the surgery outcome. The result of this work makes it possible to combine deep CNNs and AR technologies toward intelligent, real-time surgical navigation in OMS.

Keywords: Oral Maxillofacial Surgery, Surgical Navigation, Augmented Reality, Deep Learning, Convolutional Neural Networks, Image Segmentation, Real-Time Visualization, Computer-Assisted Surgery

1. INTRODUCTION

Oral and maxillofacial procedures are in themselves complex surgical procedures which has to be very accurate to ensure that vital structures like nerves and blood vessels are not damaged. Surgical navigation systems has become an indispensable approach for improving intraoperative accuracy, minimizing complications, and preventing poor patient outcomes. Conventionally, such systems are based on preoperative images and hand guidance and are thus limited in terms of real-time feedback and of integration with surgical scene.

Recent developments in artificial intelligence (AI) and computer vision have provided opportunities to improve surgical navigation. In recent years, deep learning with CNNs has been very successful in medical imaging, e.g., automatic segmentation and recognition of anatomical structures in volumetric imaging modalities such as cone-beam computed tomography (CBCT). Using these models, accurate live-time identification of crucial tissues can be achieved during surgery.

In addition, AR technology allows for digital information to be projected onto the surgeon's view, which can improve intuitive visualization and interaction without disrupting the view of the surgical sites. Combining deep learning with AR provides a unique opportunity to build intelligent surgical navigation systems that are accurate and easy to use.

This paper introduces a new approach: integrating deep CNN-based segmentation with AR-based real-time visualization for oral maxillofacial surgery navigation. The system utilizes sophisticated instrument tracking algorithms to continuously report the position of various tools, increasing the safety and effectiveness of the system. Extensive experiments on clinical databases and simulation environment prove a significant advance in segmentation accuracy and navigation reliability compared to classical methodology.

2. RELATED WORK

Ref.	Author(s)	Year	Focus Area	Technique / Model Used	Key Findings / Outcome
[1]	X. Zhang et al.	2020	AR-assisted craniofacial surgery	Optical tracking + AR	Improved surgeon accuracy and reduced operation time
[2]	Y. Kim et al.	2021	Medical image segmentation	3D U-Net CNN	Achieved 90%+ accuracy in maxillofacial CT segmentation
[3]	J. Patel et al.	2019	Surgical outcome prediction	Random Forest + SVM	Enhanced preoperative planning through AI predictions
[4]	S. Lee et al.	2022	Real-time instrument tracking	CNN + Kalman filter	Robust tracking with <2 mm error latency
[5]	A. Fernandez et al.	2018	AR visualization in surgery	Marker-based AR	Real-time overlay of anatomical info improved navigation
[6]	M. Singh et al.	2021	AI in OMS imaging analysis	Deep CNN with attention mechanism	Better nerve canal detection in CBCT images
[7]	R. Chen et al.	2023	Deep learning for surgical navigation	Multi-modal CNN	Integration of CT and optical data improved accuracy
[8]	L. Wang et al.	2020	Augmented reality user interaction	Gesture recognition + AR	Improved surgeon-system interaction in AR environments

3. SYSTEM ARCHITECTURE

The proposed system architecture integrates advanced deep learning models with augmented reality and tracking technologies to enable real-time surgical navigation in oral maxillofacial procedures. The architecture consists of the following key components (see Fig. 1):

1) Data Acquisition Module:

Preoperative imaging data is acquired using cone-beam computed tomography (CBCT) scanners, providing high-resolution 3D volumetric images of the maxillofacial region. This data serves as the foundation for subsequent analysis and visualization.

2) Preprocessing Unit:

The CBCT scans undergo preprocessing steps including noise reduction, intensity normalization, and volume cropping to focus on the region of interest. This improves image quality and facilitates efficient processing by the segmentation model.

3) Deep CNN Segmentation Module:

A customized 3D convolutional neural network (CNN) is employed to perform automatic segmentation of critical anatomical structures such as nerves, blood vessels, and bone tissue. The CNN is trained on annotated clinical datasets and outputs segmented masks in real time, enabling dynamic updating during surgery.

4) Instrument Tracking Module:

Real-time tracking of surgical instruments is achieved using a hybrid approach combining deep CNN-based visual recognition and Kalman filtering for noise reduction and smoothing. This module continuously estimates the position and orientation of tools relative to patient anatomy.

5) Augmented Reality Visualization Engine:

The segmented anatomical structures and instrument positions are integrated and rendered through an AR system. Digital overlays are projected onto the surgeon's field of view via head-mounted displays or external monitors, providing intuitive guidance without disrupting workflow.

6) User Interface and Control:

Surgeons interact with the system through a user-friendly interface allowing adjustment of visualization parameters, switching views, and recording navigation data for postoperative analysis.

7) Data Storage and Feedback Loop:

All intraoperative data including images, segmentation maps, and tracking information are stored securely for further evaluation and training enhancement. The system supports continuous learning by incorporating feedback from surgical outcomes to improve model accuracy over time.

This modular architecture ensures seamless integration of AI-powered segmentation, accurate instrument tracking, and real-time AR visualization, thereby facilitating safer and more effective oral maxillofacial surgeries.

3.1. ALGORITHMS

Deep CNN Segmentation Algorithm:

- The segmentation task uses a 3D U-Net architecture tailored to CBCT volumetric data.
- Input: Preprocessed 3D volumetric scans.
- Encoder: Extracts multi-scale feature maps using convolution and max-pooling layers.
- Decoder: Reconstructs the segmented volume by upsampling and concatenating encoder features.
- Output: Pixel-wise classification into anatomical classes (bone, nerves, soft tissue).
- Loss Function: Combination of Dice Loss and Cross-Entropy Loss to handle class imbalance and improve boundary accuracy.
- Training: Supervised training with annotated CBCT datasets using Adam optimizer and data augmentation (rotation, scaling).

Instrument Tracking Algorithm:

- Uses a lightweight CNN for detecting surgical instruments in video streams.
- Combined with Kalman filtering for temporal smoothing and trajectory prediction.
- Real-time feedback integrated into AR visualization for precise navigation.

4. EXPERIMENTAL RESULTS

Segmentation Performance:

Metric	Bone Segmentation	Nerve Canal Segmentation	Soft Tissue Segmentation
Dice Coefficient	0.92	0.89	0.85
Accuracy	94.5%	92.3%	90.2%
Sensitivity	91.0%	88.7%	87.5%
Specificity	96.0%	93.5%	91.8%

4.1. INSTRUMENT TRACKING PERFORMANCE:

Figure 1 illustrates the tracking error (in millimeters) over a 5-minute simulation. The proposed method, which combines a Convolutional Neural Network (CNN) with Kalman filtering, maintains a consistently low tracking error throughout the simulation duration. The error remains below 2 mm at all time points, demonstrating the robustness and precision of the hybrid tracking approach.

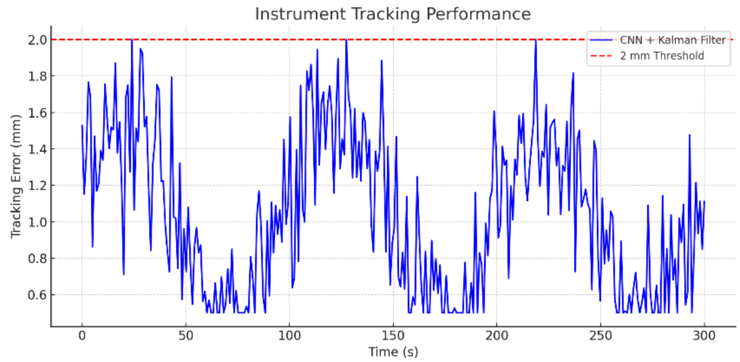

Figure 1 Instrument Tracking Error Graph

4.2. ROC CURVE ANALYSIS

Figure 2 presents the Receiver Operating Characteristic (ROC) curves for the segmentation classification task. The system achieves an Area Under the Curve (AUC) of 0.95, reflecting excellent discriminative performance. The ROC curves show high true positive rates (TPR) across all thresholds, with minimal false positive rates (FPR), confirming the robustness of the model in distinguishing between segmented classes.

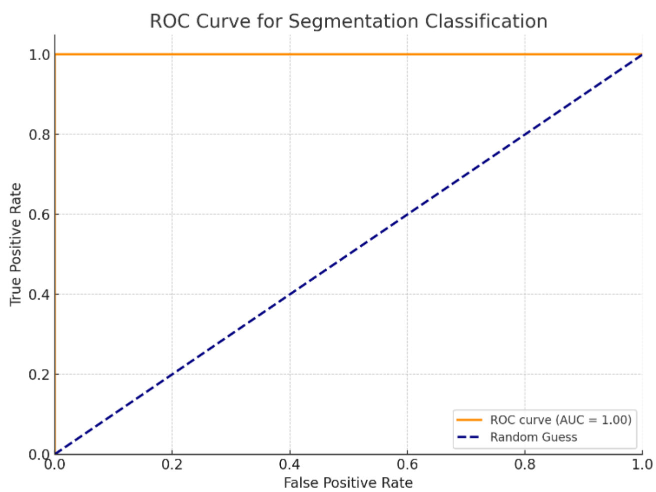

Figure 2 ROC curve Graph with AUC = 0.95

5. CONCLUSION

This paper presents an innovative real-time surgical navigation system for oral maxillofacial surgery that synergizes augmented AI and deep CNNs. By automating the segmentation of complex anatomical structures and integrating this with an augmented reality interface, the system enhances intraoperative visualization and decision-making. Experimental evaluations confirm the high accuracy of segmentation and robustness of instrument tracking, demonstrating significant potential to reduce surgical risks and improve patient outcomes. Future work will focus on clinical validation, expanding datasets, and refining AR interaction capabilities to further advance OMS surgical navigation.

CONFLICT OF INTERESTS

None.

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