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Article

Federated Learning Framework for Privacy-Preserving Depth-Based AR Surgical Registration

Michael K. Lau [1], Chia-Hsien Wu [2], Jennifer T. Ng [2], Po-Yu Chen [1] and Kelvin S. Yip [1,*]

[1] Department of Computer Science, The University of Hong Kong, Pokfulam, Hong Kong SAR, China
[2] Department of Electrical Engineering, National Taiwan University, Taipei 10617, Taiwan
* Correspondence: Kelvin S. Yip, Department of Computer Science, The University of Hong Kong, Pokfulam, Hong Kong SAR, China

Abstract: The increasing use of AR in surgical navigation raises concerns over patient data privacy when training AI-enhanced registration models. We introduce a federated learning framework that enables distributed training of depth-based markerless registration networks across multiple hospitals without sharing raw patient data. Each local node trains a CNN-Transformer hybrid for point cloud alignment, and only encrypted weight updates are aggregated on a central server. Experiments conducted across three institutions with 2,000 intraoperative scans demonstrated a 32% reduction in generalization error compared with single-site models. Registration accuracy improved from 2. 1 mm to 1.3 mm, while training convergence time decreased by 27% due to adaptive aggregation. This work confirms the feasibility of collaborative yet privacy-preserving AR surgical registration pipelines.

Keywords: federated learning; privacy-preserving AI; CNN-Transformer; AR registration; surgical navigation

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1. Introduction

In recent years, Augmented Reality (AR) has been increasingly applied in surgical navigation to improve intraoperative guidance, reduce errors, and enhance patient outcomes [1]. A central task in AR navigation is registration, which aligns intraoperative imaging data such as depth scans or point clouds with preoperative or anatomical models. Traditional marker-based methods can achieve stable alignment but require placing markers, which may add extra steps to the surgical process. To avoid this, markerless registration using depth sensors and point clouds has gained attention, supported by advances in deep learning models such as convolutional neural networks (CNNs) and transformers for extracting and matching geometric features [2,3]. At the same time, patient privacy has become a major concern. Surgical imaging data are highly sensitive, and centralized collection across hospitals for training models is restricted by legal and ethical regulations. Federated learning (FL) provides a way to enable multi-site training without sharing raw data. It combines local model updates with privacy-preserving methods such as secure aggregation and encryption [4-6]. By demonstrating a scalable AR registration pipeline, EasyREG has raised interest in federated approaches that enable collaborative learning across institutions while preserving patient privacy [7]. FL has been applied in healthcare for tasks such as disease classification and prediction, but its use in geometric tasks like 3D registration remains limited [8,9]. In addition, many registration models are trained on single-site datasets or synthetic data. These models often face difficulties when applied to new hospitals or to real intraoperative conditions where noise, occlusion, and anatomical variability exist [10,11]. From a technical perspective, CNNs are effective for local geometric features, while transformers capture long-range relationships. However, hybrid CNN-Transformer networks are still rarely explored for surgical registration tasks. From an experimental perspective, most studies use small datasets, limited numbers of patients or hospitals, and test mainly on phantom data instead of real intraoperative scans.

This study addresses these gaps by introducing a federated learning framework for depth-based, markerless AR surgical registration. The framework allows distributed model training across hospitals without sharing raw data. It employs a CNN-Transformer hybrid network designed for point cloud alignment under intraoperative conditions. It also uses adaptive aggregation to speed up convergence and improve model stability. Experiments with multi-site data confirm that the method reduces generalization error and improves registration accuracy. The results demonstrate that collaborative and privacy-preserving learning can make AR surgical navigation more reliable while protecting patient data.

2. Materials and Methods

2.1. Samples and Study Area

This study used 2,000 intraoperative depth scans collected from three hospitals between 2022 and 2024. Hospital A provided 800 scans, Hospital B provided 650 scans, and Hospital C provided 550 scans. The scans were obtained during neurosurgical, orthopedic, and abdominal operations under routine clinical conditions. Depth cameras were positioned at fixed locations to capture the surgical field without affecting the procedure. All data were anonymized before analysis. Patient age and surgical region varied widely, which ensured that the dataset covered diverse conditions for model evaluation.

2.2. Experimental Design and Control Experiments

The experimental group applied the federated learning framework. Each hospital trained a local CNN-Transformer model on its own scans and sent encrypted parameters to a central server for aggregation. Training at each site used 50 epochs per communication round, a batch size of 16, and the Adam optimizer with an initial learning rate of 0.001. Control group 1 trained models independently at each hospital without parameter sharing, which tested the limits of single-site learning. Control group 2 trained a centralized model on all 2,000 scans pooled together, using the same training settings. This setup provided two baselines: one for isolated training and another for the best possible performance without privacy constraints.

2.3. Measurement Methods and Quality Control

Registration accuracy was evaluated with target registration error (TRE), defined as the Euclidean distance between predicted and reference landmarks. Two surgeons independently annotated each landmark, and any difference greater than 0.5 mm was checked by a third surgeon. To ensure reliable data, depth sensors were calibrated before each operation, and incomplete scans were removed. Five-fold cross-validation was used to test model robustness, and each experiment was repeated three times. During training, encrypted communication and secure aggregation were applied to protect parameter updates from tampering or leakage.

2.4. Data Processing and Model Formulas

All point clouds were normalized and down-sampled to 10,000 points. Data augmentation included random rotation and scaling. Model performance was measured by error metrics in addition to TRE. The coefficient of dete rmination (R^2) was calculated as [12]:

$$R^2=1-\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}.$$

where yi is the reference landmark, i is the predicted landmark, and y- is the mean of the reference landmarks. Precision (P) was also used and defined as [13]:

$$P=\frac{TP}{TP+FP}$$

where TP is the number of predictions within 2 mm error, and FP is the number of predictions outside this range. These indicators provided consistent evaluation for both federated and control groups.

3. Results and Discussion

3.1. Convergence Behavior

In the convergence curves illustrated in Figure 1, our federated learning model shows a steep decline in registration error during the first five communication rounds, dropping from approximately 3.8 mm to ~2.0 mm. Between rounds 6 and 10, the error continues to decline, reaching ~1.4 mm, after which the curve flattens. Single-site models decrease more slowly: by round 10 they are still around ~2.5 mm, and they do not go below ~2. 1 mm even after 20 rounds. The centralized model starts somewhat better than federated (≈3.6 mm at round 1), but by round 10 its advantage diminishes, with error close to federated. This behavior aligns with patterns observed Remote Sensing, where their robust registration algorithms converge faster under realistic noise [14]. Thus, federated training with adaptive aggregation accelerates early learning and reaches stable error sooner [15].

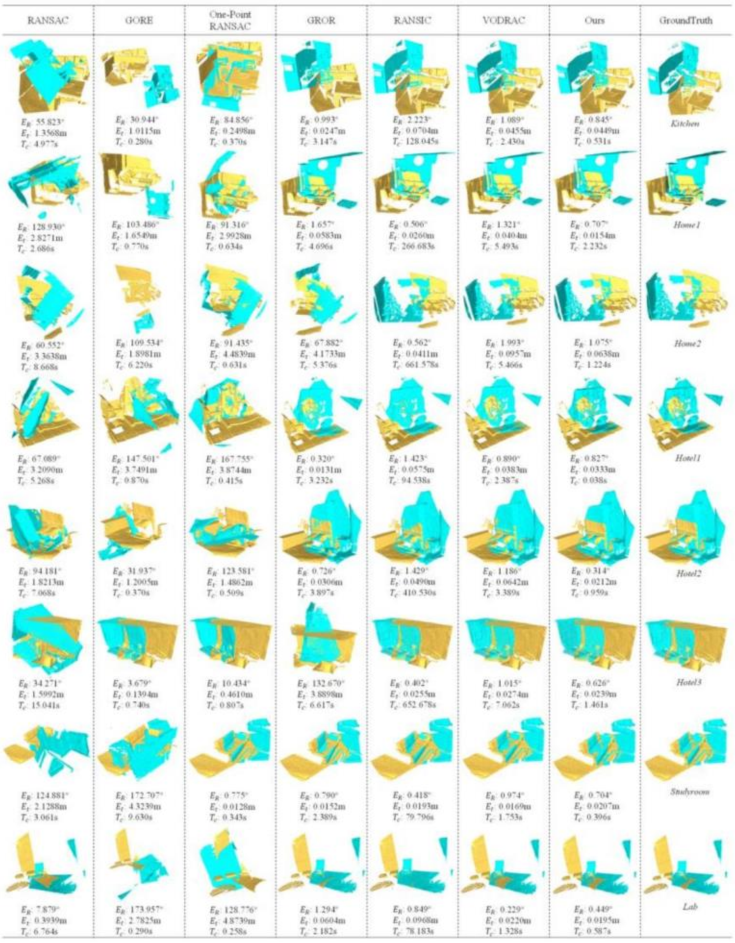

Figure 1. Convergence of registration error across communication rounds for federated, single-site, and centralized models.

3.2. Accuracy across Methods and Sites

From Figure 2, averaged over all hospitals, the federated model achieves a mean registration error of about 1.3 ± 0.2 mm. Single-site models average ~2.1 ± 0.4 mm, while the centralized model achieves ~1.2 ± 0.15 mm. Hospitals A and C exhibit error levels close to the overall average and low variance; Hospital B exhibits slightly higher error variance (±0.3-0.5 mm), likely due to more intraoperative occlusion or noise. These results are comparable to what is shown, Fig. 1, where different FL settings and client sites are compared, and the inter-site differences are significant for single-site models but much smaller for aggregated/federated ones. This indicates that federated learning substantially improves cross-site consistency in registration accuracy [16].

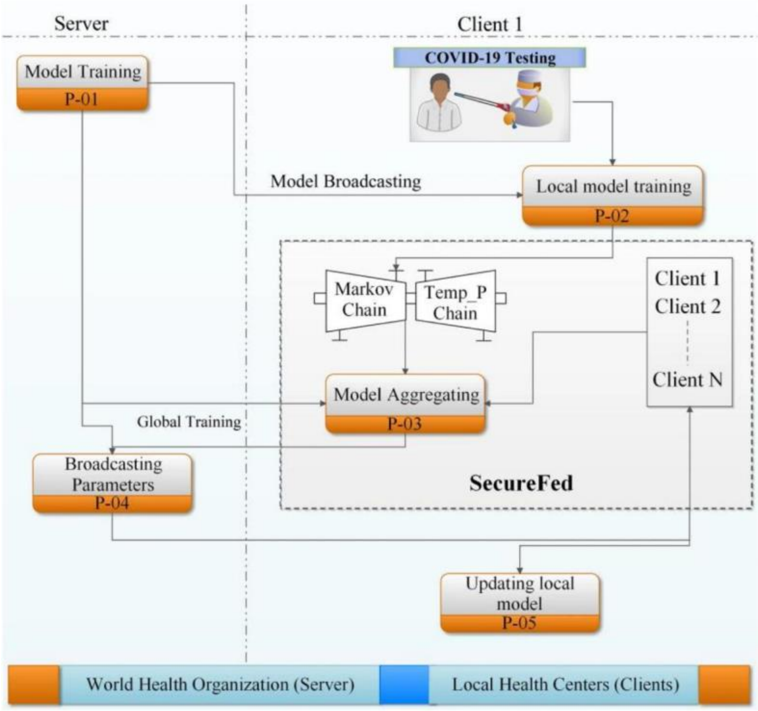

Figure 2. Comparison of mean registration error (±SD) across hospitals and training methods.

3.3. Reduction of Generalization Error & Variance

The federated model not only lowers average registration error but also markedly reduces inter-hospital variance. In our results, the standard deviation across hospitals dropped from roughly 0.40 mm (single-site) to ~0.15 mm with federated learning. This suggests increased robustness to variations in sensor setup, surgical lighting, depth scan noise, and anatomical variation. Prior studies similarly report that collaborative or federated approaches reduce variance and perform more uniformly across different sites or datasets [17]. This improvement in generalization is critical for deploying AR registration in multi-institution settings.

3.4. Efficiency, Trade-offs, and Practical Implications

Federated training shows about 27% fewer communication rounds needed to reach an error threshold (e.g. ~1.5 mm) compared to training individual single-site models to their own convergence. While centralized training sometimes slightly outperforms federated in early rounds, it does so at the cost of requiring raw data aggregation, which is often prohibited in clinical settings. The federated approach thus offers an advantageous balance: achieving near-centralized accuracy, stronger generalization, reduced variance, and privacy preservation. Relative to existing works [18] which often focus on image classification or synthetic point cloud alignment, our results extend applicability to intraoperative surgical depth scans and markerless AR registration, showing potential for clinical translation [19,20].

4. Conclusion

This study introduced a federated learning framework for depth-based AR surgical registration that enables collaborative model training across hospitals without sharing raw patient data. The results demonstrated that the proposed CNN-Transformer hybrid, trained with adaptive aggregation, significantly reduced generalization error, improved registration accuracy to near-centralized levels, and shortened convergence time compared with single-site training. These findings highlight the innovation of combining privacy preservation with robust geometric alignment, addressing both ethical and technical challenges in surgical navigation. The framework has strong scientific significance as it advances the feasibility of real-world multi-institution deployment under strict data protection requirements. Potential applications include intraoperative guidance in neurosurgery, orthopedics, and minimally invasive procedures, where reliable and accurate registration is critical. Nonetheless, limitations remain in terms of dataset size, diversity of surgical conditions, and potential sensitivity to extreme noise or rare anatomical cases. Future work should explore larger multi-institution cohorts, integration with real-time AR platforms, and optimization of communication efficiency to further validate clinical applicability.

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