Automated Integration of Surgical Implants into Digital Twins for Trauma Surgery

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Abstract. A digital twin (DT) is a dynamic virtual model that mirrors a physical system, with promising applications in surgical planning, guidance, and outcome assessment. While DTs can represent various key aspects of surgery, such as patient anatomy and surgical tools, implants remain difficult to integrate due to tracking challenges related to occlusions by soft tissue and their small size. Consequently, current surgical DTs lack implant integration, a critical limitation in trauma surgery. To address this challenge, this work presents an automated method to integrate surgical implants—plates and screws—into DTs during bone fracture platings. The solution leverages surgical tracking data to analyze interactions between surgical tools and patient anatomy. By combining deterministic algorithms with a machine learning-based activity classification model, DTs of implants can be reconstructed without requiring direct tracking. A study involving 28 participants—5 medical students, 12 residents, and 11 attending physicians—evaluated detection reliability and geometric accuracy on a comminuted ulnar fracture. Results showed a screw detection rate of 96.4 % and a plate detection rate of 100 % across 112 screws and 28 plates. Screw and plate placement had Root Mean Square Errors of 1.52 mm and 0.94 mm respectively—comparable to or better than existing surgical DTs. These findings confirm the feasibility of dynamic implant integration, marking a significant step toward comprehensive DT solutions for trauma surgery. This advancement has the potential to enhance intraoperative visualization and postoperative assessment, ultimately improving patient care.

Keywords: Digital Twin · Surgical Guidance · Implant Integration

1 Introduction

Digital twins (DTs) are virtual representations that dynamically mirror the physical state of their real-world counterpart by continuously receiving updates from data collected via sensors [11, 23]. In surgical settings, DTs model patient anatomy, instruments, staff, and the operating room using various sensing modalities [1, 5]. Patient anatomy can be reconstructed from medical imaging, such as CT and MRI [10, 24]. Instruments and staff movement can be tracked using RGB-D and infrared cameras [7, 13], while the operating room can be captured through laser scans [14]. Thereby, DTs can help to enhance patient care through various stages of surgical procedures [8, 22]. Before surgery, they enable enhanced planning by simulating patient-specific anatomies [9] and provide a risk-free training environment for practice [6, 9, 12]. During surgery, they can support clinical decision-making by offering 3D visualizations to surgeons [3, 18, 17, 21] and can serve as the basis for navigation in robot-assisted surgery [15, 12, 6]. Post-surgery, they enable the collection of detailed records of outcomes, supporting post-operative decision-making [2, 16]. Recent studies have demonstrated such concepts in various surgical fields by successfully modeling patient anatomy and surgical instruments [21, 19, 20]. Hein et al., in their proof-of-concept study, were even able to create an entire digital environment from a spinal surgery that included patient anatomy, instruments, staff, and the operating room using multiple sensor modalities [14].

However, a key limitation of current DT implementations in surgery is the exclusion of surgical implants, which are essential in trauma procedures such as fracture fixation with screws and plates. The lack of implant integration in DTs arises from two key challenges: (1) reliable tracking is difficult due to occlusion by soft tissue, and (2) even when visible, their small size makes accurate tracking challenging—particularly for screws. To address this, we propose an indirect approach that eliminates the need for direct implant tracking. Instead, a standard tracking system to monitor reliably trackable instruments and bone fragments is used. By analyzing their interactions with deterministic algorithms and machine learning models, the placement of screws and plates is dynamically reconstructed within the DT.

To assess the feasibility of this method, a study involving 28 participants, including 5 medical students, 12 residents, and 11 attending physicians, was conducted using a phantom setup where they performed a bridge plating for a comminuted ulnar fracture. It was evaluated how many of the surgical plates and screws could be recognized and how accurately their placement compared to their physical counterpart was. The results demonstrate that the proposed solution can (1) reliably detect surgical implants and (2) accurately reconstruct their placement within DTs. This, in turn, enhances the clinical utility and integration potential of DTs in trauma surgery for plating procedures across different anatomical locations—such as the distal radius, proximal humerus, or tibial shaft—and ultimately improves patient care.

2 Methods

2.1 Digital representation of tools and bones

The proposed workflow—illustrated in Fig. 1—incorporates positions and orientations (6D poses) of drills, screwdrivers, and the two primary bone fragments retrieved by a surgical tracking system. This data is continuously transmitted to a Unity 3D game engine, running at 120 Hz. The 6D pose information is then applied onto corresponding 3D meshes, which are generated through 3D scanning for surgical instruments and CT segmentation for bone structures. This process enables the real-time digital representation of surgical tools and bones.

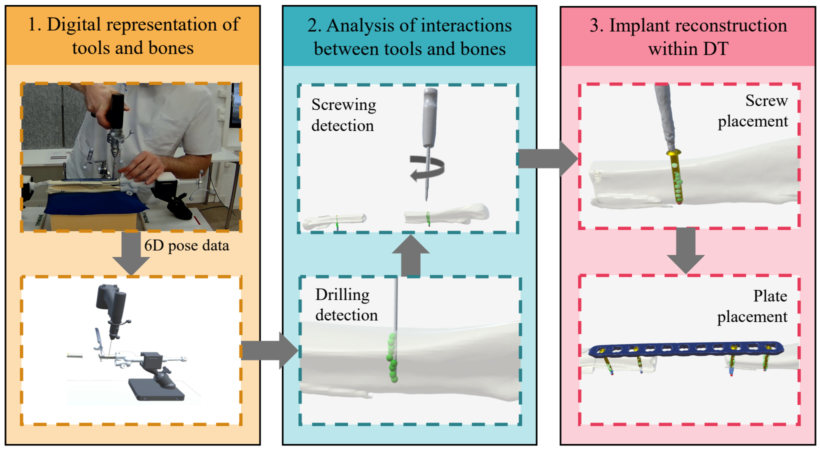


Fig. 1: Overview of the implant reconstruction pipeline. Digital representation of tools and bones is obtained via 6D pose estimation. Tool–bone interactions are analyzed: drilling is detected via deterministic methods, screwing is classified using an LSTM model. Based on these interactions, DTs of screws and plates are reconstructed without requiring direct implant tracking.

2.2 Analysis of interactions between tools and bones

Drilling detection Before a screw can be placed, a drill hole must be created, which is recognized using a deterministic approach. These drill holes establish reference trajectories along which screws can be positioned. A drilling trajectory is generated within the DT once the drill tip advances through the cortex of a bone fragment. The action is classified as drilling while forward motion continues and the traversed volume is marked accordingly. Drilling is considered complete when the drill retracts fully along its axis and exits the bone. The trajectory is estimated using linear least squares regression minimizing the deviation from the drilled volume.

Screwing detection Unlike drilling, screwing cannot be detected through direct interaction with the bone, as the screwdriver does not physically engage with the tracked bone fragments. Therefore, a probabilistic approach is employed, using a Long Short-Term Memory (LSTM) network to detect screwing activities—screwing in, unscrewing, or other actions—at 30 Hz. The implementation of the screwing detection model is explained in Fig. 2.

2.3 Implant reconstruction within DT

Screw placement A screw is instantiated in the DT when the screwdriver's longitudinal axis aligns with a drill hole, and the screwing detection model predicts a screwing-in activity. The screw length is determined via raycasting from the screwdriver tip to the bone surface. Once created, the screw is rigidly attached to the corresponding bone fragment to ensure synchronized movement. If screwing-in is detected, the screw advances with the screwdriver; if unscrewing is recognized, it retracts, provided the screwdriver tip remains in contact with the virtual screw head. This process determines both screw length and insertion depth.

Plate placement Once the third screw is placed, plate positioning is initiated within the DT, beginning after a detected screw-driving activity. A point-set registration aligns the plate by matching its holes to the positions of the set screws. Since the correspondence between screws and plate holes is initially unknown, a brute-force search assesses all possible screw-to-hole mappings. The configuration that minimizes the average distance between plate holes and screws after alignment is selected. As a final optimization step, the plate is rotated along its longitudinal axis to ensure its surface orientation aligns with the average longitudinal axis of the screws.

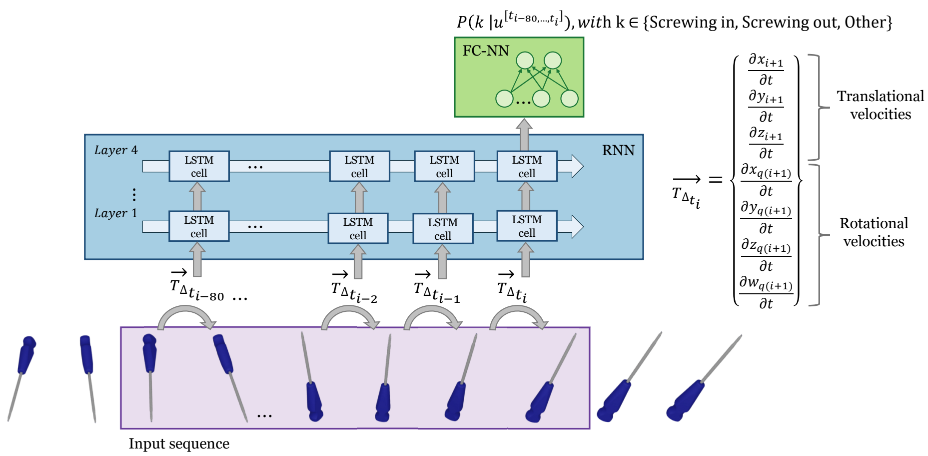


Fig. 2: The screwing detection model consists of a 4-layer unidirectional LSTM, followed by a fully connected classification layer. Input features—translation and rotation velocities from screwdriver tracking—are downsampled to 60 FPS and processed in 80-frame sequences with a window shift of 2, yielding an output frequency of 30 FPS. The model was trained using the Adam optimizer and CrossEntropyLoss. Training data consisted solely of 1 hour of engineer-recorded activities, while validation was conducted in a phantom setup with 2 hours of recordings from 11 surgeons, achieving 96.6 % accuracy and an F1-score of 90.9 %

3 Experimental Setup

This experiment aimed to evaluate the detection reliability—percentage of correctly identified screws and plates—and the geometric accuracy of implants within the DT reconstructed using the proposed method. The study was conducted with a phantom setup, in which 28 participants—5 medical students, 12 residents, and 11 attending physicians—performed the procedure. All participants provided informed consent, and the study was conducted in accordance with ethical guidelines.

3.1 Hardware and Phantom Setup

A phantom setup with synthetic bones (Synbone AG, Switzerland) simulating a comminuted right ulnar fracture was used. The bones were secured in a custom holder for anatomically realistic positioning, which can be seen in Fig. 3a. The Atracsys Fusion Track 250, an operating room-certified navigation system, provided tracking input. The 3D meshes of the surgical tools were obtained using a handheld 3D scanner (Shining 3D, China), while the 3D meshes of the synthetic bones were derived from CT scan segmentation. Markers were mounted on both the surgical tools and bone holders. An Iterative Closest Point algorithm was used to align the tracking markers with their corresponding 3D models and determine their relative poses. All data were processed on a CPU (11th Gen Intel(R) Core(TM) i7-1165G7).

(a) (b)

Fig. 3: a) Phantom Setup with synthetic bones secured in a custom holder and b) tools used to perform the procedure equipped with fiducial markers

3.2 Procedure

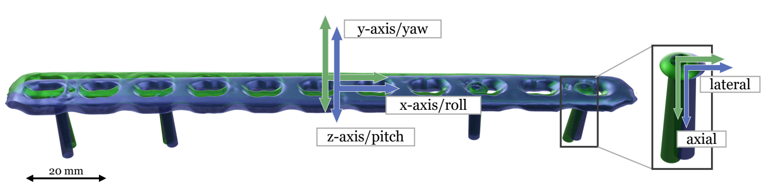
All participants followed the same standardized protocol. Before performing the training case, they were instructed via a video. The video was designed in accordance with the AO fracture management principles—AO Classification 22C1 [4]— to demonstrate the treatment of a comminuted ulnar fracture using a bridge plate. Additionally, written instructions were provided in front of the training setup to guide participants through the procedure. The tools required for the procedure were placed on a separate table next to the setup, as shown in Fig. 3b. The participants used these tools independently without assistance. Assistance was only provided when selecting screws, to ensure that participants received the desired screw length.

3.3 Evaluation

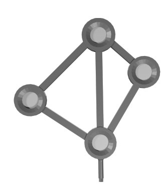
To assess the accuracy of the reconstructed DTs of the implants, their positions were compared to precise ground truth measurements obtained using the Atracsys Fusion Track 250 navigation system. The ground truth screw positions were measured using a custom-designed marker (see Fig. 4b) that fits precisely into the screw drive, enabling accurate capture of both position and orientation along the longitudinal axis. Additionally, all lengths of the selected screw were manually reported. The ground truth plate position was determined via point-set registration, where reference points were collected using a pointed marker and aligned with their corresponding digital reference points. The reconstructed DT was then compared to the ground truth measurements illustrated in Fig. 4a.

Screw placement accuracy was evaluated by measuring: (1) positional deviation along the screw's longitudinal axis (axial shift) and perpendicular to the longitudinal axis (lateral shift), (2) angular deviation between the reconstructed and measured longitudinal axes (axial angle), (3) deviation from the digitally estimated to the effectively recorded screw length, and (4) the Root Mean Square Error (RMSE) of all points between reconstructed and measured screw surfaces.

Plate placement accuracy was evaluated by measuring: (1) positional deviation along the x, y, and z axes, (2) angular deviation between the reconstructed and measured plate orientations in terms of pitch, yaw, and roll, and (3) the RMSE of all points between reconstructed and measured plate surfaces.



(a)



(b)

Fig. 4: a) Implant placement accuracy evaluation, showing the reconstructed DT (blue) and ground truth DT (green) and b) custom-designed marker to measure ground truth of the screws

4 Results

All 28 procedures were successfully completed and included in the evaluation. In total, 112 screws (28 × 4 per procedure) and 28 plates were placed. Examples of digitally reconstructed twins can be seen in Fig. 5

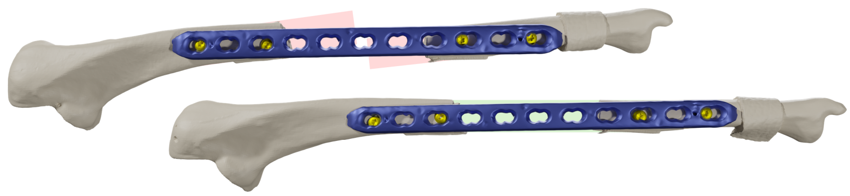


Fig. 5: Study examples of DTs with unsuccessful and successful plating

4.1 Detection rates

Of the 112 placed screws, 108 were correctly detected, yielding an average detection rate of 96.4 %. All 28 plates were correctly identified.

4.2 Geometrical accuracies

Screws Evaluation of screw placement accuracy in Fig. 6 shows an average lateral deviation of 2.18 mm and an average axial deviation of 1.07 mm. The angular deviation between the reconstructed and measured longitudinal axes averaged 5.0°. The deviation from the digitally estimated to the effectively manually recorded screw length was on average 0.85 mm. The RMSE between reconstructed and measured screw surfaces was 1.52 mm.

Plates Evaluation of plate placement accuracy in Fig. 6 shows an average absolute positional deviation of 2.37 mm. The angular deviation between the reconstructed and measured plate orientations in terms of pitch, yaw, and roll averaged 1.6°. The RMSE between reconstructed and measured plate surfaces was 0.94 mm.

5 Discussion & Conclusion

The study's results demonstrate the feasibility of the proposed method for integrating implants into DTs for trauma surgery. The high detection rates for both plates and screws across all procedures demonstrate the reliable reconstruction of implant DTs. The four undetected screws (out of 112) can be attributed to tracking failures caused by hand occlusions of the markers. An accurate reconstruction of the DTs of implants could be demonstrated, with a low RMSE for

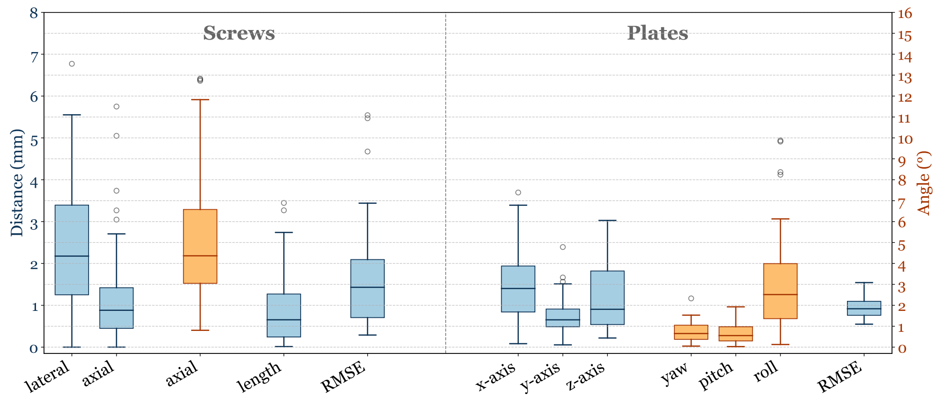


Fig. 6: Accuracies of reconstructed DTs, screws (left) and plates (right).

screws (1.52 mm) and especially for plates (0.94 mm). Plate positioning was particularly precise, as it was derived from multiple detected screw positions, allowing individual screw errors to average out and reducing overall deviation. In contrast, screws exhibited a slightly higher RMSE due to greater deviations in lateral positioning and axial angles. This likely lies in the assumption of rigid behavior for the drill bit and the bone fragments, whereas in practice, slight elastic deformations occur during drilling. Additionally, minor registration errors between tracking markers and tools contribute to deviations.

Comparison with previous studies further underscores the method's accuracy. The RMSE between reconstructed and measured implant surfaces is comparable to the 1.39 mm error reported by Shu et al. for the DT of a patient anatomy [21] and substantially lower than the 6.84 mm error reported by Hein et al. for the DT of a surgical environment [14]. This demonstrates that the proposed method can effectively complement existing DT solutions, providing a more complete digital representation of the surgical setting. Beyond intraoperative visualization and guidance, the proposed method for implant reconstruction in DTs holds significant potential for postoperative applications. DT data can support finite element method analyses to assess implant stability and guide treatment strategies, as suggested by Aubert et al. [2]. Notably, this approach eliminates the need for additional intraoperative imaging or postoperative CT segmentation, allowing seamless integration into existing clinical workflows.

Future work should focus on validating the proposed method in real surgical environments, such as cadaveric studies or clinical trials. A key challenge in clinical settings is the occlusion of tracking markers due to crowded operating rooms and soft tissue. To address this, future research could explore markerless tracking or the integration of complementary sensing modalities to ensure robustness. To enhance intraoperative utility, the current workflow, where plate reconstruction begins only after the third screw, is a limitation. Future work could extend the method to enable earlier plate estimation, providing more timely feedback during surgery. Research could also investigate integration into augmented reality systems or robotic workflows to assess its impact on surgical precision and efficiency. Additionally, future studies could examine how reconstructed digital twins support postoperative outcome assessment in plating procedures. Another promising direction is their use in simulation-based training, where DTs may provide objective, scalable performance feedback for surgical education.

In conclusion, this work presents a novel method for integrating surgical implants into DTs for trauma surgery, demonstrating reliable and precise implant reconstruction. Using an indirect approach, surgical tracking can be leveraged to reconstruct implants within DTs by analyzing interactions between surgical tools and patient anatomy, eliminating the need for unfeasible direct implant tracking. The method represents a significant step toward comprehensive DT solutions with potential benefits in intraoperative guidance and postoperative assessment, ultimately improving patient care.

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